AD A046006

(6) STRATEGIC IMPLICATIONS OF THE EXPERIENCE CURVE EFFECT FOR AVIONICS ACQUISITIONS BY THE DEPARTMENT OF DEFENSE. (3)

(9) Final rept.,

A Thesis

Submitted to the Faculty

of

Purdue University

by

(10) William Fitch Cheney IV

In Partial Fulfillment of the

Requirements for the Degree

of

Doctor of Philosophy

(12) 310p.

(11) August 1977

ACKNOWLEDGMENTS

I wish to express my appreciation to Dr. Arnold Cooper, my major professor, for his patience, encouragement, and cogent advice throughout this research effort. The constructive criticism provided by Dr. James Buck, Dr. Edgar Pessemier, and Dr. Dan Schendel, my advisory committee members, was especially valuable. Within the Air Force, special thanks are due to Major Lyle Lockwood of the Air Force Business Research Management Center, Mr. Kent Ricker of the Air Force Systems Command's Aeronautical Systems Division, and Mr. Robert Downing of the Air Force Logistics Command's Warner-Robins Air Logistics Center. Without their sponsorship and support, this research could not have been undertaken.

Thanks are also due to Babs Pounds for her professional typing of this work. Finally, I wish to thank my wife, Betty-Anne, and our six children for their tolerance, encouragement, and cooperation throughout this research effort.

SECURITY CLASSIFICATION OF THIS PAGE (*When Data Entered*)

REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (*and Subtitle*) Strategic Implications of the Experience Curve Effect for Avionics Acquisitions by the Department of Defense		5. TYPE OF REPORT & PERIOD COVERED Final - Ph.D. Dissertation
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) William Fitch Cheney, LTC, USAF		8. CONTRACT OR GRANT NUMBER(s)
9. PERFORMING ORGANIZATION NAME AND ADDRESS Purdue University West LaFayette, IN 47902		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME AND ADDRESS Air Force Busi Research Mgmt Center (AU) Wright-Patterson AFB, OH 45433		12. REPORT DATE August 1977
		13. NUMBER OF PAGES 306
14. MONITORING AGENCY NAME & ADDRESS (*if different from Controlling Office*)		15. SECURITY CLASS. (*of this report*) Unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (*of this Report*)

Unlimited

17. DISTRIBUTION STATEMENT (*of the abstract entered in Block 20, if different from Report*)

18. SUPPLEMENTARY NOTES

Prepared under the auspices of the Air Force Business Research Management Center.

19. KEY WORDS (*Continue on reverse side if necessary and identify by block number*)

Learning Curve	Procurement Planning
Experience Curve	Avionics Procurement
Acquisition Strategy	Production Planning
Procurement Strategy	Production Strategy
Acquisition Planning	The Department of Defense (DoD)

20. ABSTRACT (*Continue on reverse side if necessary and identify by block number*)

The Defense Department has supported numerous studies of learning curve theory, mainly in the context of the aircraft and airframe industries. However, no research has yet been documented with respect to experience curve theory (as distinguished from learning curve theory) for either buyers or sellers in the relatively ~~unique~~ (specialized) environment of the military market place. This dissertation describes investigations into the applicability and strategic implications of the experience curve effect for Defense

(cont over)

DD FORM 1 JAN 73 1473 EDITION OF 1 NOV 65 IS OBSOLETE

PII Redacted

SECURITY CLASSIFICATION OF THIS PAGE (*When Data Entered*)

(controver) → DoD

Department avionics purchases. it also recognizes

While Experience curve theory seeks to explain product cost-quantity and price-quantity relationships in terms similar to those of learning curve theory, ~~but recognizing~~ the influences of such managerially controllable factors as investment, specialization, and scale.

The most significant finding of this study confirmed the applicability of experience curve theory in the military market place in spite of the unique characteristics of that market (i.e., cumulative average unit price parallels cumulative average total manufacturing cost).

Recommendations for future research and for procurement actions are also provided.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Cheney, William Fitch, IV. Ph.D., Purdue University, August 1977. Strategic Implications of the Experience Curve Effect for Avionics Acquisitions by the Department of Defense. Major Professor: Arnold C. Cooper.

The Defense Department has supported numerous studies of learning curve theory, mainly in the context of the aircraft and airframe industries. However, no research has yet been documented with respect to experience curve theory (as distinguished from learning curve theory) for either buyers or sellers in the relatively unique environment of the military market place. This dissertation describes investigations into the applicability and strategic implications of the experience curve effect for Defense Department avionics purchases.

Experience curve theory seeks to explain product cost-quantity and price-quantity relationships in terms similar to those of learning curve theory, but recognizing the influences of such managerially controllable factors as investment, specialization, and scale. Experience curve concepts are usually associated with strategic planning and decision making, and with development of an organization's goals and policies. Experience theory relates highly aggregated cost or price data and production quantity data to gain insights into the actions and interactions of manufacturing firms.

Several related issues were investigated, using power form models, bivariate and multivariate regression techniques, and standard

statistical tests (e.g., t-tests, chi-square). The data base analyzed, representing 20 equipment items and 13 contractors, consisted of price and quantity information on 361 Air Force avionics procurements (1960-1976); cost and delivery schedule information were also available for 237 of them.

The most significant finding confirmed the applicability of experience curve theory in the military market place in spite of the unique characteristics of that market (i.e., cumulative average unit price parallels cumulative average total manufacturing cost). Inflation adjusted price reductions associated with doubled cumulative production quantities were typically in the range of 5% to 15%, substantially less than the 20% to 30% reductions observed by other researchers in consumer and industrial products markets. This gradual rate of experience realization is apparently due both to the extent of Government interventions and controls and to the concern of military procurement officials for maintaining flexibility at the expense of productivity. Comparisons of alternative inflation treatments confirmed that analytical results were only slightly affected by a choice among deflators based on Gross National Product, Federal Purchases of Goods and Services, and Avionics Procurement indices; use of any of these deflators gave consistently better analytical results than ignoring inflation.

Consideration of production parameters in a multiplicative power form model along with cumulative quantity improved explained price variance and reduced standard error of estimate. Production Break Duration, Delivery Lead Time, and Maximum Delivery Rate were found to be the most significant modulating parameters, followed by Average

Delivery Rate and Quantity Bought. Experience slope change patterns were identified in 15 of 32 production sequences evaluated, based on segmenting overall price-experience curves. The slope of the final segment was typically 6% steeper than the corresponding overall slope. Regression slopes were found to be highly variable, both across products within firms and across firms for like products, suggesting that the use of firm or industry averages is likely to be misleading. Price predictions based on segmented data were consistently better than those based on total data.

Recommendations for future research and for procurement actions are also provided. Emphasis is placed on increasing form, fit, and function standardization and investing in process technology to increase military procurement productivity.

This research was sponsored by the U.S. Air Force.

CHAPTER I — INTRODUCTION AND OVERVIEW

This dissertation describes investigations into the applicability and strategic implications of the experience curve effect for avionics acquisitions by the Department of Defense. Experience curve theory seeks to explain product cost-quantity (or price-quantity) relationships in terms similar to those of learning curve theory, but recognizing the influences of such managerially controllable factors as investment, specialization, and scale. This theory has far-reaching strategic implications for many aspects of business, with the most significant centering on the dependence of profitability on market share. Department of Defense procurement agencies can improve their own strategic decisions by recognizing and considering the implications of the experience curve effect for aerospace industry firms. Avionics (aviation electronics) acquisitions were chosen to provide the data base for the present research because of the author's extensive prior knowledge of this area and continuing sponsorship by the U.S. Air Force.

Subsequent sections of this introductory chapter will provide the reader with overviews of the experience curve effect, its implications for business strategy, and the nature of procurement strategy decisions common to the Department of Defense. These sections will be followed by an explanation of the significance and focus of the present research, and a description of the organization of the balance of the dissertation.

The Experience Curve Effect

Although the terms "experience curve" and "learning curve" were used interchangeably from World War II to the early 1960's, an increasingly clear distinction has been drawn between those terms since the mid 1960's. The experience curve concept proposes that the costs of value added to a product generally decline by from 20 to 30 percent in real terms (i.e., inflation adjusted) each time accumulated experience with the product is doubled. This relationship is usually represented mathematically by the same power form model as has been used for over forty years to represent the learning curve (explained at length in Chapter II):

$$Y = A\,X^{B} \qquad (1)$$

where Y represents cost, X represents the cumulative number of units produced, A is a parameter reflecting the imputed cost of the first unit produced, and B is a parameter reflecting the rate at which experience is being gained. By analogy to the mathematical characteristics of the learning curve, this 20 to 30 percent decline corresponds to a slope of 80 or 70 percent, respectively, for a logarithmically transformed curve which plots as a straight line on full logarithmic graph paper. The simplicity of this traditional model is the chief justification for its widespread use. Due to this simplicity, and to Government and industry familiarity with the model from its learning curve applications, it will be used for much of the present research. (Two slightly more complex variants will be introduced later and used for parts of this work.)

In spite of the mathematical similarity to the power form model for learning curves, the experience curve concept is far broader than learning curves. Near one end of a spectrum of possible applications, learning curve theory is most often applied in projecting the direct costs (in labor hours or dollars) of value added to a manufactured product by direct labor, and is based on the idea that manual skills improve predictably with increased task repetitions. Near the opposite end of this applications spectrum, experience curve concepts are usually associated with strategic planning and decision-making, and with the development of an organization's goals and policies. Experience theory considers such strategically controllable factors as investment, specialization, and scale, in addition to learning. Experience theory is applied at higher levels of cost aggregation, where the costs of value added include at least indirect labor and various overhead charges, not just the direct labor costs of learning theory.

Strictly interpreting the underlying theory, experience effect costs should be taken to be cash flows, rather than accounting costs, in order to more directly recognize the effects of the cost of capital and of return on capital. However, market prices have been found to be a suitable and much more readily available surrogate for cash flows in numerous empirical studies. The experience concept has been successfully applied to reflect both individual firm and industry level price-quantity interactions for a variety of consumer and industrial products.

Not surprisingly, the experience curve concept has been found to work best in those situations where its existence and validity are acknowledge , and managers then take positive actions to optimize the benefits realizable from their understanding of the concept, through manipulating investment, specialization, and scale factors. Whereas the equilibrium conditions of classical economic theory are static, indicating for instance that there is a finite minimum cost which is a function of scale, the experience effect theory is dynamic, suggesting that such a finite minimum exists only at a point in time.

Key implications of the experience effect for business strategy are presented in the next section, with emphasis on the areas of price and competitive interaction, technology and market share, product growth rate, new product introduction, and procurement negotiations.

Implications for Business Strategy

Empirical evidence on consumer and industrial products indicates that prices tend to follow the same pattern as costs, provided that the relationships amongst competitors are stable. When prices do not follow costs, the relationships among competitors become increasingly unstable. When prices decline less rapidly than costs, profit margins grow and new competitors are encouraged to enter the market place. After an unacceptable level of overcapacity develops, price competition commences, prices fall more rapidly than costs, and marginal producers are eliminated in the ensuing shakeout. When equilibrium is regained, the relatively few surviving competitors will be realizing smaller profits, but with the most experienced competitor continuing to receive more than a pro rata share of the profits.

Alleged technological gaps may, in actuality, be instead experience gaps. Investment in research and development to exploit technology permits firms to introduce new products and improve on existing ones faster than their competitors who did not undertake similar investments. Experience contributes to profitability, which facilitates technology exploitation, which in turn leads to the realization of added experience, and hence increased profits. There does not appear to be any naturally stable relationship amongst competitors until one of them commands a controlling market share and the product's growth slows. When stability for a particular product is achieved, each competitor's profitability will be a function of his accumulated experience both with that product and with closely related ones. Thus capturing a dominant market share, leading to the greatest accumulated experience, should lead to the greatest profits.

A close analogy may be drawn between product growth rate and compound interest. The more rapidly a company expands production, the sooner it will gain substantial added experience, thus reducing costs and enhancing profitability. It is normally far easier to capture market share by capturing the growth in an industry, rather than by displacing competitors' shares in a stable industry. Empahsis should therefore be placed on investing heavily to capture a dominant market share in rapidly growing markets, rather than on attempting to gain significant market share in low growth, stable, or declining markets.

When new products are introduced, it may often be desirable to set their price initially at or below cost. The lower the introductory price set by the product's first producer, the faster that producer can

build volume and gain experience, thus reducing his costs. If prices are then reduced with costs, allowing for only a small profit margin, competitors will be discouraged from entering the market, since their initial investment would have to be greater just to catch up. Of course, the lower the introductory price, the greater the investment of the initial producer must be, and the greater will be his risk in the event the product is unsuccessful.

The insights available to purchasers from consideration of the experience curve effect are particularly advantageous for establishing price negotiation objectives, determining possible price stability in terms of both level and duration, and designing the reward and penalty features of incentive contracts. However, potential restrictions on realization of these insights come in two forms: 1) Since experience curve theories are based on constant-value dollars, inflation effects should be excluded; and 2) Experience curves are not necessarily applicable when major elements of cost or price are determined by monopolies, Government regulations, or natural resource limitations. Both of these potential restrictions will be treated at length in the course of the present research.

While there are many similarities between industrial subcontracting and Government contracting, there are also many differences. The Defense Department, as the principal purchaser of aerospace industry products, is faced with its own set of strategic decisions with respect to procurement alternatives. These will be highlighted in the next section.

Defense Procurement Strategy Decisions

There are two basic, competing goals facing defense procurement decision makers: 1) Obtain essential capabilities at minimum cost, and 2) Maintain the industrial flexibility and innovative potential to be able to respond rapidly to changing threats. The first of these goals may best be satisfied through policies favoring standardization, minimizing the assortment of items procured and encouraging competition only in situations in which it may be expected to reduce life-cycle costs. (Life-cycle costs include costs of development, production, deployment, operation, and logistic support for the planned life of an item.) On the other hand, the second of these goals may best be satisfied through policies discouraging standardization, increasing the assortment of items procured and encouraging competition even when it increases costs.

In seeking an appropriate balance between these two competing goals, defense procurement decision makers are faced with numerous alternatives. Typical questions addressed preparatory to awarding costly or critical defense subsystem procurements, such as for avionics subsystems, are discussed next.

With respect to standardization, the first question is whether or not an existing design can provide the required capabilities. If it cannot, can an existing design be modified to satisfy the need? If modification is not practical either, then new development is indicated. Even though new development normally requires more time and money than continuation or modification of an existing design, it may sometimes be justifiable solely on the grounds of maintaining industrial flexibility and developing innovative capability.

With respect to competition, Federal law requires that Government contracts be awarded competitively insofar as practical. While negotiated competition is usually found to be practical for the initial procurement in a sequence of buys of a particular subsystem design, questions often arise as to whether competition should be maintained (or if not maintained, reintroduced) on subsequent buys. Important considerations here include comparative life-cycle cost projections (both with and without competition), and the likelihood of needing an alternative production source at some future time.

In preparing life-cycle cost projections, the potential effects of changes in several production parameters must be considered. For instance, how will procurement costs be affected by changes in lot size, delivery lead time, average and peak delivery rates, and the duration of breaks in production? Understanding of interactions amongst these parameters also contributes to the definition of an appropriate contract structure (e.g., contract type, incentives, options) and to the formulation of realistic negotiation objectives. Clear understandings of the relationships between costs and prices, of the effects of alternative inflation treatments, and of the merits and weaknesses of alternative forecasting techniques are likewise essential.

The likelihood of needing an alternative production source is a subjective assessment, but it is based largely on business considerations. These include a firm's managerial and technological capabilities, its economic health, its prospects for future growth or decline, its susceptibility to acquisition, and the strategic importance it attaches to defense business.

The present research has been designed to contribute to an improved understanding of business and Government procurement strategy options. It involves the analysis of empirical data on avionics subsystem acquisitions, and interpretation of the analytical results in the light of experience curve theory. The significance of this research topic and the focus of the present research are described in the next section.

Significance and Focus of Research

The Defense Department has supported numerous studies of learning curve theory, mainly in the context of the airframe and aircraft industries; several of these studies will be mentioned in Chapter III. However, no research has yet been documented with respect to the applicability or significance of experience curve theory (as distinguished from learning theory) for either buyers or sellers in the relatively unique environment of the military market place.

Department of Defense procurements impose very extensive Government regulations on contractors, and the few-sellers, very-few-buyers (oligopolistic, oligopsonistic) defense market place differs markedly from the strongly competitive consumer and industrial markets examined in the light of experience curve theory by The Boston Consulting Group (1972) and by Woolley (1972). For instance, defense procurements are usually made only in annual increments, authorized and funded at the discretion of Congress. The uncertainty thus surrounding future orders is a severe disincentive to capital investment, resulting in less than optimal efficiency and productivity. Productivity enhancement is

further handicapped by the particularly rapid onset of obsolescence, unfortunately characteristic of the high technology products required by the defense community. Long lead-times between major project startup and completion are the rule, not the exception. Non-standard designs are common, and the contractor's technical risks are multiplied by Government intervention in both product and process design changes. Although regulations imposed by the Government impact most contractors in such areas as safety, labor standards, and financial reporting, defense contractors are also subjected to stringent Government controls on quality, security, subcontracting, and documentation. Defense urgency often dictates unusually demanding delivery schedules, cutting delivery lead-times and severely constraining preproduction planning actions.

The Defense Department budget for fiscal 1977 provided for procurement spending of over $20 billion for new weapons systems, supporting a defense-related industry employment estimated to involve 1,750,000 workers (Berry, 1976). Consideration of the applicability and implications of experience curve theory in the context of this huge market seems clearly overdue.

In seeking to gain new insights into the potential benefits of experience curve theory, seven related issues are investigated, each in the context of selected Department of Defense avionics equipment procurements made within the past seventeen years (i.e., 1960 through 1976). Each of these questions will now be briefly introduced.

Issue 1: How do experience curves differ from traditional learning curves in the Government procurement environment? Experience

curves may be viewed as an approximation to the summation of a whole set of learning curves, individually applicable to the elements which collectively comprise a particular product. At varying levels of aggregation of these subsidiary learning curves, the experience effect may be reflected in the direct costs of value added (the traditional learning theory view), in total manufacturing costs, in total costs, or in market price (most convenient for strategic analysis). In view of the unique characteristics of the defense market place, as distinguished from consumer and industrial markets, it is appropriate to compare cost-based learning curves at various levels of aggregation with price-based experience curves, to determine the degree to which the experience effect pertains in these constrained market conditions.

Issue 2: How are the forms of experience curves affected by alternative techniques for compensating for the effects of inflation? Various techniques may be employed for compensating for the effects of inflation, ranging from ignoring inflation entirely to applying implicit deflators closely tailored to a particular industry or procurement environment. Ignoring inflation entirely would simplify analyses, but could lead to erroneous inferences. Applying broadly based deflators (derived from Gross National Product indices) has been the standard approach in previous analyses. Applying closely tailored deflators would seem to be more appealing, but might not affect the slopes of experience curves (and thus the inferences made from them) enough to warrant the added analytical complexities introduced. It is important to identify an approach which provides an appropriate balance between analytical simplicity and inferential power.

Issue 3: How are the forms of experience curves affected by implicit prior experience on closely related products? New products are frequently variants of older products, often incorporating components, subassemblies, and manufacturing processes with which the manufacturer has already attained extensive experience. Extended production breaks can create situations in which resumed production should not be treated as a totally new start. Rather, credit should be given in some way for implicit prior experience, recognizing that the current production is not totally new, and that not all prior experience has been lost.

Issue 4: How are the forms of experience curves related to production lot sizes, product delivery rates, delivery lead-times, and the durations of breaks between production runs? The traditional power form model of experience does not explicitly consider such factors as investment, specialization, and scale. The production parameters considered here have been selected as implicit indicators of those experience components, based both on traditional economic theory with regard to their effects and on the availability of consistently measurable data. A better understanding of the effects of these parameters on price in a dynamic procurement environment would be particularly useful in developing life-cycle cost projections.

Issue 5: How stable are experience curve slopes over successive procurements? It seems reasonable to expect changes in experience curve slopes from one period in a product's life cycle to another, due for instance to advancing product and process maturity, to competitive interactions, or to changes in production scale. If such

changes occur, the overall experience curve might be better represented by piecewise log-linear segments. Especially for short-term projections, bivariate regression on log-linear segments (if applicable) should offer a simpler and more accurate tool than multivariate regression.

Issue 6: How consistent are experience curve slopes within and across firms? It is common practice when forecasting the experience pattern of a new product to use the slope value for a similar product within the firm or industry, or in some cases even to use firm or industry average values. The question arises as to whether or not it is reasonable to apply an experience slope observed on one product or class of products within a firm to projections of the probable behavior of other products. Further, it is expected that enough differences do, in fact, exist from one firm to another to raise serious doubts about the validity of using industry average experience slopes as representative of individual firms' capabilities.

Issue 7: How accurately can future procurement pricing be predicted using experience curve theory? It is generally recognized that the theory of experience curves seeks to emphasize the inferences which can be made at a strategic level, rather than to support specific detailed estimates or projections of costs or prices. However, it may be feasible to extract such projections from knowledge of recent market prices and various factors influencing production. The simplicity associated with forecasting from price-based data augmented by relatively insensitive contractor characteristics would make such a price projection technique valuable.

The organization of the balance of the dissertation will be described in the remaining section of this chapter.

Organization of Dissertation

In the next chapter, industrial engineering oriented views of the mathematics and philosophy of learning theory are presented. The section on mathematics is of the greater importance, since traditionally the same formulas have been used to represent experience curve theory. The extensive background on learning theory is considered relevant to the present research because learning theory is usually recognized as the dominant component of experience theory.

The third chapter traces the historical development of learning and experience curves, establishing in greater detail the basis for the experience curve effect. The literature review focuses attention on areas which have been relatively neglected or otherwise incompletely treated in prior research, and in particular on those aspects of previously published work which contributed to formulation of the present research effort.

In the fourth chapter, the research methodology is explained. The research is organized around the seven issues identified in the preceding section of this introductory chapter. In addition to further discussion of each of the research issues, the chapter presents hypotheses to be tested, analytical models and procedures to be used, and statistical tests to be employed in the course of the analyses.

The avionics procurement data base developed from proprietary Government sources to support the present research is described in

the fifth chapter. Additionally, the alternative inflation adjustments applied to that data base are explained.

The sixth chapter presents the results of this research, including discussions of findings and the related inferences drawn from those findings. The structure is parallel to that of the fourth chapter, again organized around the seven issues already identified.

In the final chapter, overall conclusions and recommendations based on the research are provided. In addition to recommendations for future academic research, recommendations are also proffered with regard to future actions by both buyers and sellers in the defense market place. Supporting tables and figures not critical to the narrative development of the dissertation have been relegated to appendices.

CHAPTER II — PHILOSOPHY AND MATHEMATICS OF LEARNING

Industrial engineering oriented views of the mathematics and philosophy of learning theory are presented in this chapter. The section on mathematics is of the greatest importance, since the same formulas are commonly used to represent experience curve theory. This extensive background on learning theory is considered relevant to the present research because learning theory is usually recognized as the dominant component of experience theory. Experience theory, however, permits explanation of many of the perturbations and anomalies common to learning theory in terms of the additional experience factors of investment, specialization, and scale; these latter factors are not considered in this chapter.

The Learning Phenomenon

It has often been demonstrated that, when a new task is undertaken, repeated performance of that task will improve the efficiency with which it is accomplished. The efficiency of performance seems to improve most rapidly in the first few repetitions, and increasingly more gradually thereafter. It might seem reasonable to believe (particularly in cases of relatively simple manual labor) that, after a given number of repetitions of a task, learning would cease and a peak level of efficiency would be attained. However, in the power form learning curve theory, the contention is that the proportional

amount of learning (or percentage of increase in efficiency of task performance) is constant for proportional numbers of task repetitions. The implication of this contention is that learning is a continuous process, and that no finite limit to learning is ever reached, regardless of the number of repetitions. While at first glance this concept might appear to be illogical, the key to rationality of the theory is the emphasis on proportional repetitions.

Measuring the rate of learning (or even obtaining conclusive evidence that learning is indeed taking place) becomes exceedingly difficult in situations where the task is simple and the rate of learning is quite low. But where the task becomes more complex, and where more than one person is required for its performance, the rate of learning is generally far greater, and consequently fewer repetitions are needed to permit confirmation and measurement of learning. In view of this, it would seem reasonable to expect the initial isolation and measurement of the learning curve phenomenon to have occurred in an industry which: 1) Required a large amount of direct labor, 2) Produced complex products in moderate quantities, and 3) Produced products which changed frequently, thus creating more opportunities to observe initial learning on new products. Naturally enough, the U.S. airframe industry of the 1920's and 1930's (to which these characteristics pertained) was the industry in which the learning curve phenomenon was first accurately measured.

The initial observation and measurement of the learning curve phenomenon is sometimes credited to Leslie McDill who conducted original research leading to development of the learning curve theory.

His work was done in 1925, while he was the commanding officer at McCook Field (now part of Wright-Patterson Air Force Base) near Dayton, Ohio. However, the first publication of this theory apparently did not occur until 1936, in an article by T. P. Wright of the Curtiss-Wright Corporation (Wright, 1936). In his article, which was based on fourteen years of research on aircraft production data, Wright presented theories regarding the learning curve phenomenon which are still valid today. Thus, in view of the durability of his published theories, Wright is more frequently cited by current authors as the originator of learning curve theory.

From the mid-1930's, following publication of Wright's article, through the mid-1940's, most airframe companies recognized, and made varying uses of, learning curve theory. Following World War II, however, it was given wide practical application to production functions other than direct labor within the airframe industry, and was also introduced to a wide variety of other industries. More recently, researchers have established evidence of the learning curve phenomenon existing (but not being recognized) in the petroleum, steel, and electric power industries as far back as 1888. The general applicability of learning curve theory to a wide spectrum of industrial endeavors, particularly those relating to repetitive manufacturing functions, is now broadly recognized and accepted. Recent extensions of learning curve theory to the more encompassing concept of experience curves, however, are still largely viewed as developmental and unproven.

A variety of factors have been cited by numerous authors as being responsible for, or contributing to, the learning phenomenon: worker

learning, designer learning, production planning, scheduling, tooling, sequencing of operations, synchronization of functions, ordering of materials in proper sizes and quantities, better use of materials to mininize waste, specialization, worker morale, rejection and rework reduction, increased lot sizes, and reduced quantity of engineering changes (e.g., Asher, 1956; Colasuonno, 1967; Orsini, 1970). While worker learning is often considered to be the dominant factor in short run performance improvement, efficient and dynamic management is recognized as essential for sustained long term improvement. One of the commonest arguments proffered to refute the validity of learning curve theory is that savings attributed to learning do not just occur naturally, but rather are made to occur through the exercise of management controls. To the degree to which the imposition of management controls forces increased efficiency, learning curve theory is indeed self-fulfilling prophecy. However, this fact in no way diminishes the utility of learning curve theory as a valued tool for prediction and forecasting.

Mathematical Characteristics of Learning Curves

The principal advantages of representing the learning phenomenon by mathematical expressions and curves are: 1) The learning rate and theory can be expressed in absolute terms, facilitating continuity and consistency of application, 2) A mathematical basis is provided for projecting and measuring anticipated rates of learning beyond the range of historical data, and 3) The mathematical representation permits application and manipulation of the learning curve theory using computer techniques.

The traditional form of the mathematical expression representing the learning or experience curve phenomenon is

$$Y = A\,X^{B} \tag{1}$$

where Y represents cost (or price, or labor hours, etc.), X represents the cumulative number of units produced, A is a parameter reflecting the imputed cost of the first unit produced, and B is a parameter reflecting the rate of learning. Equation (1) is referred to as a power form model or power function, and demonstrates an inverse variation relationship (Y decreases in value as X increases) for the normal range of values of B (i.e., $-1 < B < 0$). Figure 1 depicts the arithmetic graph of a representative learning curve relation:

$$Y = 100\,X^{-0.32193} \tag{2}$$

It should be noted that, when equation (1) is used to represent the learning phenomenon, the resultant curves may be variously referred to as cost-quantity curves, cost reduction curves, efficiency curves, experience curves, improvement curves, learning curves, performance curves, production acceleration curves, or progress curves. While the mathematical formulation is identical for each, different authors and practitioners attribute slightly different meanings to the individual names.

If the traditional power form of the learning curve is expressed logarithmically, an important transformation in the statement of the relationship between X and Y occurs:

$$\log Y = \log\,(AX^{B}) = \log A + B \log X \tag{3}$$

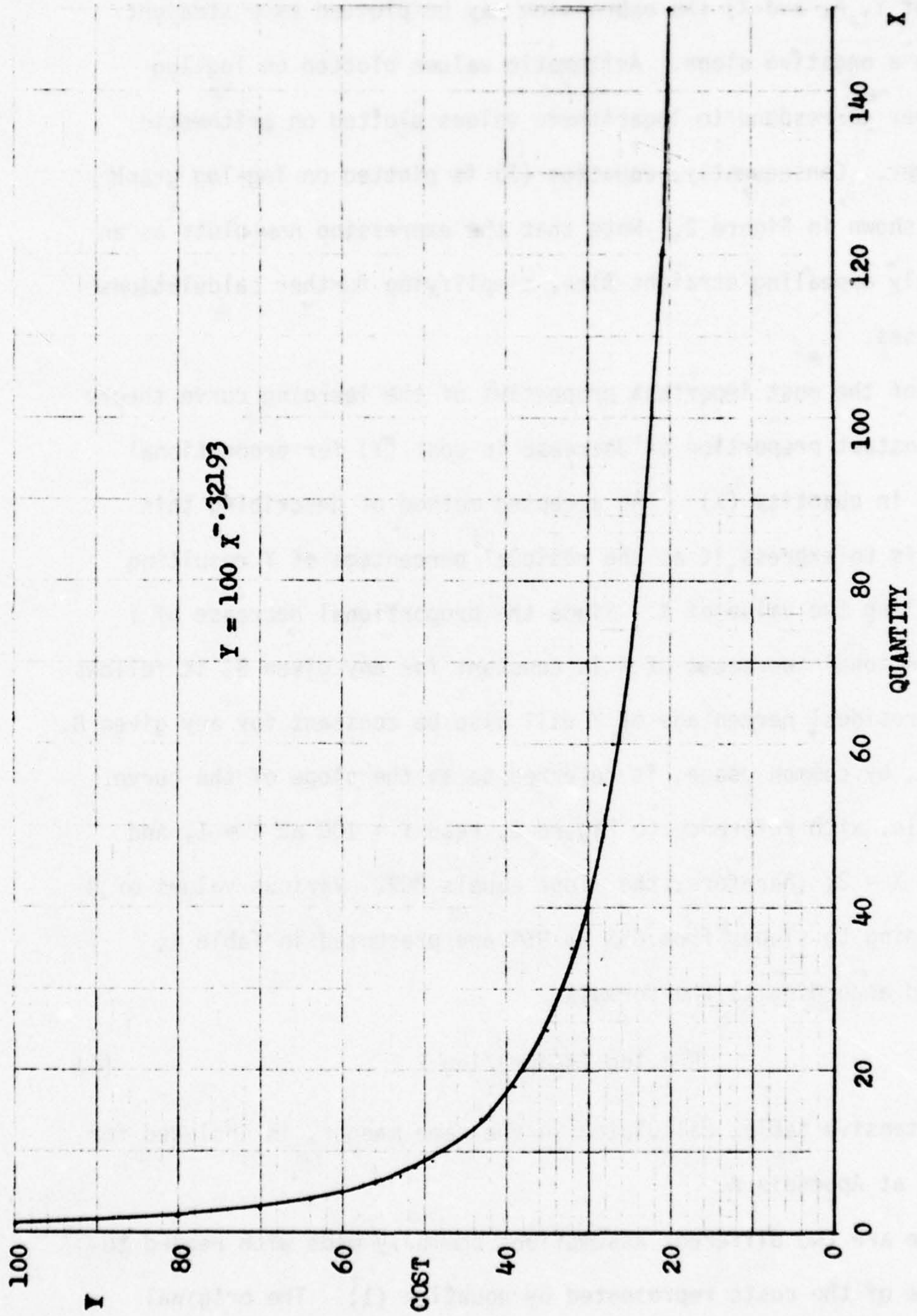


FIGURE 1 — ARITHMETIC GRAPH OF A LEARNING CURVE RELATION

Since B is a negative constant, it is apparent that for logarithmic values (of Y, A, and X) the expression may be plotted as a straight line with a negative slope. Arithmetic values plotted on log-log graph paper correspond to logarithmic values plotted on arithmetic graph paper. Consequently, equation (2) is plotted on log-log graph paper as shown in Figure 2. Note that the expression now plots as an intuitively appealing straight line, simplifying further calculations and analyses.

One of the most important properties of the learning curve theory is the constant proportion of decrease in cost (Y) for proportional increases in quantity (X). The accepted method of describing this decrease is to express it as the residual percentage of Y resulting from doubling the value of X. Since the proportional decrease of Y for proportional increases of X is constant for any given B, it follows that the residual percentage of Y will also be constant for any given B. This term, by common usage, is referred to as the slope of the curve. For example, with reference to Figure 2, read Y = 100 at X = 1, and Y = 80 at X = 2; therefore, the slope equals 80%. Various values of B corresponding to slopes from 65% to 95% are presented in Table 1, calculated according to the formula

$$B = \log (\text{slope})/\log 2 \tag{4}$$

A more extensive table, calculated in the same manner, is included for reference at Appendix A.

There are two different assumptions commonly made with regard to the nature of the costs represented by equation (1). The original

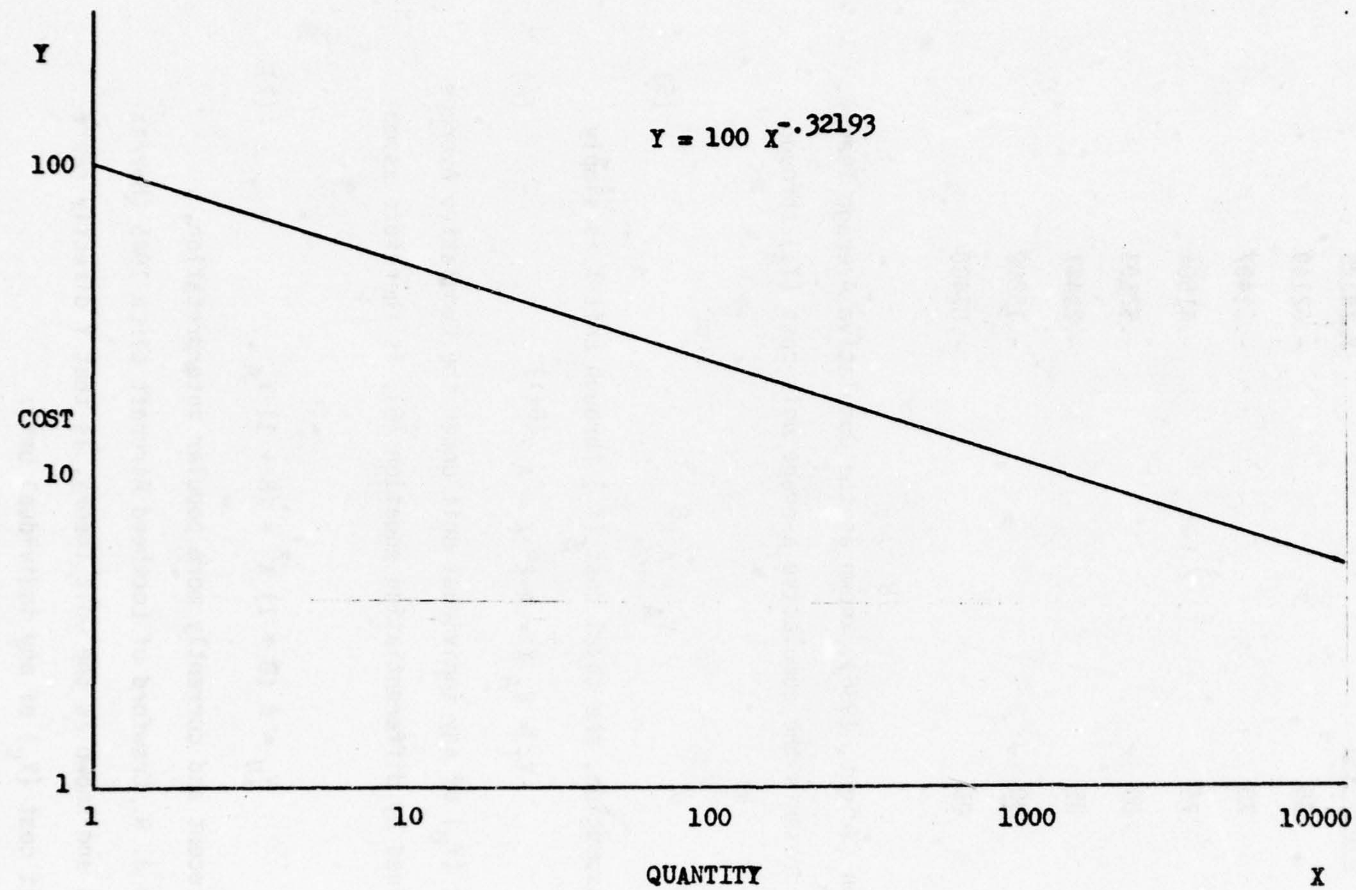


FIGURE 2 — LOGARITHMIC GRAPH OF A LEARNING CURVE RELATION

TABLE 1 — B VALUES FOR VARIOUS SLOPES

Slope (%)	B Value
65	-.62149
70	-.51457
75	-.41504
80	-.32193
85	-.23447
90	-.15200
95	-.07400

interpretation (Wright, 1936), known as the Cumulative Average Theory, was that Y represents the cumulative average unit cost (Y_A) through unit X:

$$Y_A = A\, X^B \tag{5}$$

Under this assumption, the total cost (Y_T) through unit X is simply

$$Y_T = Y_A\, X = A\, X^B\, X = A\, X^{(B+1)} \tag{6}$$

The unit cost (Y_U) of any individual unit under the Cumulative Average Theory, obtained by differentiating equation (6), is therefore asymptotic to

$$Y_U = A\,(B + 1)\, X^B = (B + 1)\, Y_A \tag{7}$$

A more recent and currently more popular interpretation, attributed to J. R. Crawford of Lockheed Aircraft circa 1945 (Harris et al., 1965) and known as the Unit Theory, is that Y directly represents the unit cost (Y_U) of any individual unit:

$$Y_U = A\,X^B \tag{8}$$

Under this assumption, the total cost (Y_T) through unit X, obtained by integrating equation (8), is given by

$$Y_T = \frac{A}{(B+1)}\,X^{(B+1)} \tag{9}$$

The cumulative average unit cost (Y_A) under the Unit Theory is thus asymptotic to

$$Y_A = \frac{A\,X^{(B+1)}}{(B+1)\,X} = \frac{A}{(B+1)}\,X^B = \frac{1}{(B+1)}\,Y_U \tag{10}$$

Consequently, regardless of the theory assumed to hold, the unit cost (Y_U) will be less than the cumulative average cost (Y_A) due to the constant factor (B + 1). Figure 3 depicts these relations graphically, and shows that the asymptotic values are good approximations of the true values except for small values of X.

In Chapter III, the relative merits of the two learning curve theories will be brought out, and the error introduced by the asymptotic approximation of unit cost or average cost values will be discussed. Another point of confusion, that of selecting the appropriate values of X, referred to as lot midpoints, for plotting curves when only lot average data are available and the Unit Theory is considered to pertain, will also be clarified. (The algebraic lot midpoint is the unit number which represents the average unit cost of the lot.)

Extensive tables have been prepared to facilitate learning curve computations by practitioners without ready access to computers. For instance, the RAND Corporation has published a three volume set of

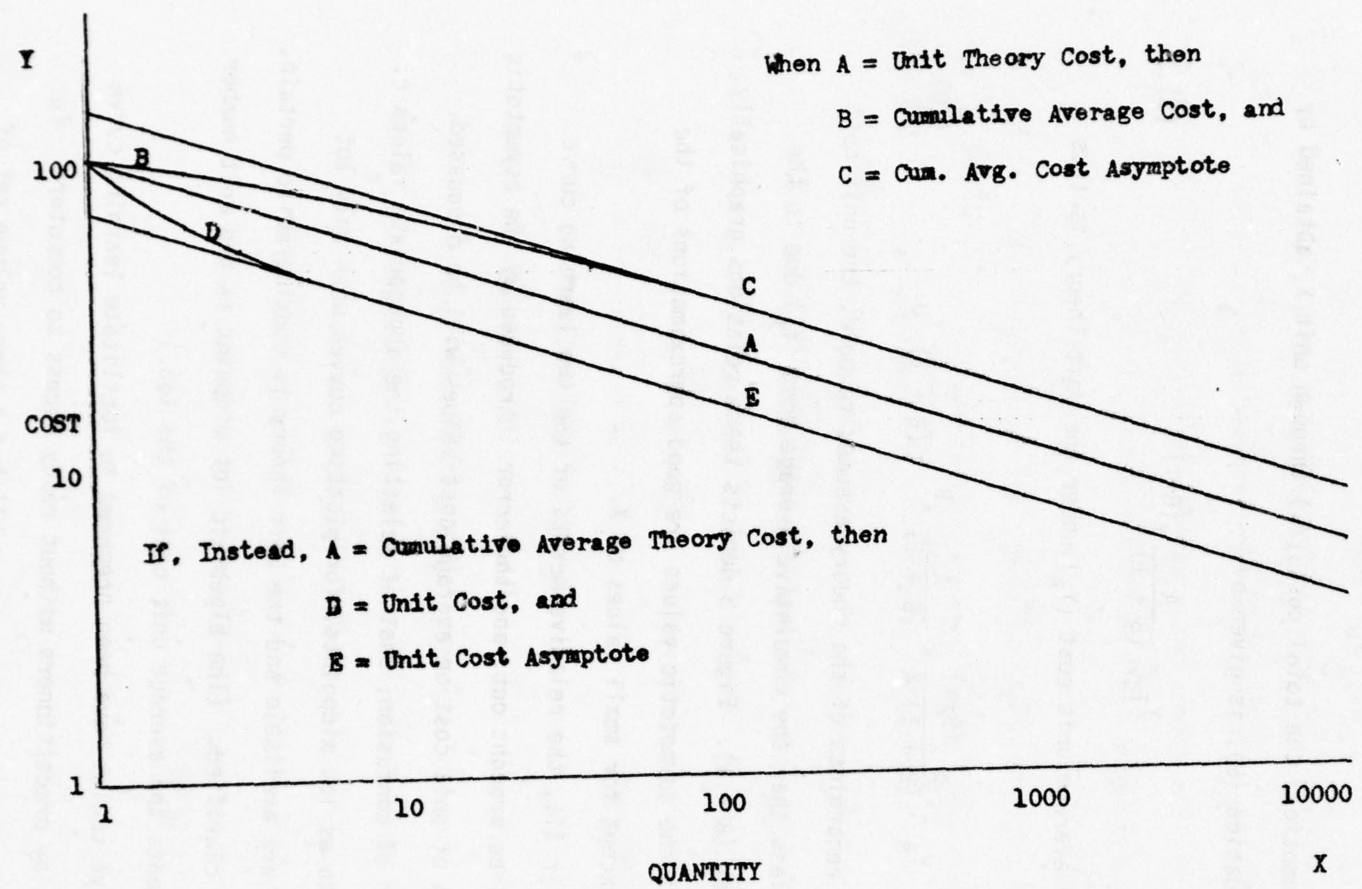


FIGURE 3 — ALTERNATIVE THEORY COMPARISONS

tables (Boren and Campbell, 1970) for learning curve slopes from 55% through 99% and lot sizes of from 1 through 2000 units. For each slope and lot size, for both the Cumulative Average Theory and the Unit Theory, the tables provide lot midpoints, cumulative total costs, cumulative average costs, and unit costs.

Industry Uses of the Learning Curve

The principal application of learning curve theory, both in industry and in the Government, has been as an aid for cost estimating. Manufacturing cost components have commonly been segregated as: direct labor costs, overhead costs, material costs, engineering and tooling costs, general and administrative costs, and subcontracting costs. The collective response of these cost components to various rates of learning is reflected in the composite learning which determines product cost and cost variations.

Throughout much of the production cycle of most complex labor-intensive products, direct labor costs represent the largest individual cost component. There is overwhelming empirical evidence, particularly in the airframe, ship-building, and machine tool industries, that direct labor costs do, in fact, decline proportionally as the cumulative number of units produced increases. This reduction is properly represented by the expression of equation (1). While the values of the constants vary widely from one product to another, even within one industry (with resultant variations in the height and slope of unit cost and average cost curves), the overall average direct labor unit cost curve has been found to have a slope of approximately 80%. It

must be emphasized that this is an overall average; individual products may have characteristics differing quite significantly from this average. The underlying cause for such variations is readily apparent: while learning can be expected to take place in all manual labor activities, the rate and amount of learning applicable to fabrication, subassembly, or final assembly work (as examples) will differ significantly, depending on such factors as the prior learning base at the outset of the task, the skill of the work force, and the proportion of total direct labor required for the specific activity.

Overhead is customarily expressed as a percentage of direct labor costs. However, although some overhead costs do indeed vary fairly directly with labor costs, others do not: taxes, depreciation, and executive salaries, as examples. Consequently, it is apparent that overhead is expressed as it is because of precedent and convenience, rather than because the percentage relationship is truly an accurate representation. Since overhead rates vary widely, commonly in a range from 100% to 200% of direct labor costs, the proportion of product cost attributable to overhead cannot be confidently identified without detailed knowledge of the product, the manufacturer, and the industry. Because the traditional practice of considering overhead to be a fixed percentage of direct labor costs has proven to be generally workable, it has become acceptable to assume that the same rate of learning (approximately 80% on average) applies to overhead as applies to direct labor.

Material costs have generally been found to follow a much more gradual learning curve, with an overall average slope on the order of 95%. Again, the elements of material purchases (raw material, fabricated parts, subassemblies, etc.) differ in their respective rates and amounts of learning with respect to any given product. The reasons most often cited for material cost adherence to some form of learning curve include: 1) Economic order quantities, 2) Purchasing in increasingly efficient forms (e.g., shapes, sizes), 3) Less waste and reduced rework and rejections, and 4) Reduced handling.

Engineering and tooling costs have commonly been viewed as predominantly non-recurring sunk costs, and little attention has thus been given to establishing an empirical relationship between these costs and learning theory. There are indications, however, that sustaining engineering efforts during production (i.e., production engineering support continuing throughout a run) do indeed benefit from the learning phenomenon, as the engineers become increasingly familiar with the product and the tooling. Since the engineering problems encountered during production seldom recur in nearly identical form, the rate of learning associated with these engineering efforts is generally slower than that associated with the direct labor effort on the same product, but substantially faster than that associated with the product's material costs.

General and administrative costs normally include the costs of such functions as contract administration, legal and audit expenses, marketing expenses, and other costs allocated to, rather

than directly identified with, the products manufactured. In a manner similar to the traditional treatment of overhead, general and administrative costs are usually computed as a percentage, but of total production costs rather than of direct labor costs. Learning theory thus does not directly apply on a product by product basis, although certainly such functions as contract administration, legal, audit, and marketing can be expected to demonstrate some learning over time. Since the proportion of product costs attributable to allocation of general and administrative expenses is generally small, little error is introduced by assuming that learning in this area approximates that experienced with direct labor.

Subcontracting costs have been found to vary roughly in proportion to total product costs, dependent mostly upon the prime contractor and type of contract. Limited empirical evidence suggests that higher proportional amounts of subcontracting generally cause flatter learning curves and higher total costs. This conclusion is not really unexpected, since the more work is spread out, the fewer opportunities exist to benefit from concentrated learning. When the components of subcontracting costs are spread across the other standard components of product manufacturing costs (direct labor, overhead, material, tooling and engineering, and general administrative), it is usually found that subcontract learning rates are roughly comparable to those of the prime contractor, but that total costs remain relatively high because the limited amount of work subcontracted limits learning opportunities of each individual subcontractor.

For a given product, the composite learning which determines product cost and cost variations is a result of the combination of the various learning rates associated with each component of manufacturing cost, weighted in accordance with the relative significance of each such component in the manufacture of that product. In general, for labor intensive products, the effective composite learning rate approaches that for direct labor; for capital intensive products, the effective composite learning rate is more likely to approach that for material costs.

The principal advantage from assuming cost adherence to the learning curve derives from the fact that future costs may be predicted by projection of the mathematically described curve. Industry and elements of the Government dealing with industry have used the predictability of learning theory in a variety of ways. The main Government applications of learning theory are found in cost estimating and in contract cost auditing and control. Industry, however, applies learning curves more widely. It must be noted that the learning curve is not, and should not be, used in isolation. Historical production data, industrial engineering factors, and management judgment are also critical inputs to most learning theory applications.

Industry uses of learning theory center on the following functions: costing, scheduling, purchasing, budgeting, and management control. As already stated, the principal application of learning theory has been as an aid for the first of these functions, costing. Cost estimating is a particularly critical function of companies contracting with the Government because of the increased emphasis on competitive

bidding, fixed-price-incentive contracts, and firm-fixed-price contracts. Even though contractor bids are usually based on detailed labor and material estimates, learning theory provides a valuable tool for validating these estimates. Commercially, as well as in dealing with the Government, knowledge of a competitor's rate of learning is particularly advantageous in establishing competitive prices.

The direct labor learning curve is of key importance in scheduling. Since it can help to provide reasonable estimates of labor requirements at any point in the production cycle, it facilitates hiring and transferring of employees, and distribution of work across multiple shifts on an optimal basis. Knowing the approximate number of manhours required per unit of production also permits efficient scheduling of plant facilities, determination of optimal tooling configurations, and adjustment of delivery rates in an economically advantageous manner.

Purchasing agents take advantage of learning theory when dealing with suppliers, using their estimates of the effect of learning on supplier capabilities as a key factor in establishing their negotiating positions. The learning curves for raw materials and for standard fabricated parts are often already at high cumulative production numbers, thus limiting the learning benefits which may be derived. However, when parts or materials to be supplied are new or complex, there is generally significant opportunity to benefit from the effects of learning theory.

Budgeting of resource expenditures (manpower and material, as well as money) and scheduling of resource acquisitions are greatly simplified by the application of learning theory. Alternative budgets can be planned in considerable detail prior to the initiation of a production program, with a most likely budget being pursued initially, and a more appropriate budget being selected and implemented once initial production confirms the rate of learning (i.e., the effective slope of the learning curve) actually being achieved. Further refinements can be made as work progresses, entailing only shifts amongst preplanned alternative budgets, rather than development of completely new ones.

Management control techniques within industry also benefit from learning theory applications. Knowledge of a company's potential learning rate, based on demonstrated performance on previous production of comparable products, gives the company's management a powerful tool for work force control. The rate of production, efficiency of the work force, and costs or parametric costs of various stages in product fabrication and assembly, can all be estimated in advance, and used as standards or guides for assessing the actual effectiveness of the company's employees. Conversely, the learning theory also permits measurement of management effectiveness, since it is a function of management to assure that production efficiency attains and maintains a high level. Here again, a note of caution must be sounded: To the degree to which the imposition of management controls forces increased efficiency, learning theory is indeed self-fulfilling prophecy.

Government Uses of the Learning Curve

Government uses of the learning curve, particularly within the Department of Defense and the National Aeronautics and Space Administration, center on both long range and short range cost estimates, contractor cost and schedule control during production, and estimates of the cost sensitivity of changes in the mix of forces. Rapid advancements in the state of technology, the increasingly high costs of weapons systems, and the long lead times required for acquisition of ever more complex weapons systems, all contribute to the urgency of the National need for timely and accurate long range estimates of force mixes and defense postures. Because learning theory is based on historically consistent data, and because it can be mathematically projected well beyond the range of available data, it is a particularly worthwhile and highly valued tool for long range cost estimating.

This applicability of learning theory is further enhanced by the fact that the major consideration in evaluating the costs of alternative future weapons (or space systems, etc.) is usually comparison, which is even more dependent on the consistency of estimating techniques than on their detailed accuracy. Since many vital elements affecting the cost of future weapons systems are usually unknown (e.g., inflation, raw material availability), emphasis in long range estimating is placed on the selection of techniques other than detailed engineering estimates. Estimating techniques should be simple to apply, and should lead to reproducible results. Techniques should be equally applicable to all systems considered in a force mix. Finally, techniques should be adaptable to computer implementation and manipulation. Learning curve

equations, derived from bivariate regression of historical data, satisfy these criteria well. Learning theory is reasonably simple, it applies to a broad spectrum of products and weapons systems, and it can be readily programmed for computer applications. While it is recognized that careless or indiscriminate projection of learning curves can lead to large errors, learning theory appears to be one of the best tools currently available for minimizing the risks of long range estimating.

As applied by the Government as a tool for short range cost estimating, learning theory is used mainly in conjunction with the award of production contracts, usually to validate or refute a contractor's detailed labor and material cost estimates. This is of necessity a subjective application, with the values of constants chosen on the basis of the judgment which the Government's estimator makes of a given contractor's previous performance and past and projected production capacities, tempered by knowledge of representative learning curve slopes within industry for comparable products. Government estimators seldom have either the staff support of the historical data to reconstruct detailed cost estimates. Consequently, primary reliance is typically placed on evaluation and assessment of contractors' proposals. However, since thorough evaluation is dependent on having considerable knowledge of each contractor's estimating techniques, production capacities, and accounting systems, the Government seldom takes a firm negotiating position solely on the basis of the results of analyses based on application of learning theory.

Once a Government system acquisition contract is awarded, learning theory is normally employed as a key tool in the continuous evaluation and analysis of the contractor's cost and schedule performance. On the basis of Government interpretation of contractor provided data, actual learning rates being realized are determined early in the production program. Government managers then compare their assessments of actual learning with precontract estimates and with contract terms, and encourage contractors to minimize those variances which are viewed as disadvantageous to the Government. Principal emphasis is usually placed on parametric cost curves, such as direct labor man-hours, rather than on actual dollar figures. Again, learning theory is only one of many tools used, and is commonly applied in conjunction with other standard management tools, tempered by the experience, knowledge, and judgment of the Government program manager.

Measuring the cost sensitivity of changes in a force mix through the application of learning theory is peculiar to the Department of Defense, except for limited use by the National Aeronautics and Space Administration. (There appears to be some similarity, however, with industrial applications of learning theory as a tool for determining optimal product-market mixes.) Once a National defense posture has been assumed and a specific force mix established, the number and type of weapons systems in the force are constantly subject to change for a variety of reasons. Prime amongst these are changes in the enemy threat, rapid technological advances, and economic considerations. Estimation of the relative cost impact of various possible force mix changes is essential, and is largely dependent on the application of

learning theory. Learning curves have been found to be particularly useful for estimating the cost for increasing the quantity of particular weapons systems already in production or operation. Estimates are based on projections of key component costs of the production of those weapons systems, or in some instances on projections based only on the prices previously paid for them.

Factors Restricting Learning Curve Applicability

No two learning curves representing actual production programs are exactly alike. The values of the constants (A and B) for each major cost component of each product vary widely, not only between the different components, but also between the same components for different products. Direct labor learning curves for different products are good examples. Although the broad industry approximation of an 80% slope has been widely cited as representative, the slopes of the individual direct labor curves for various products are broadly distributed about that average. Variations caused by random upward or downward fluctuations in lot costs are generally minor, and tend to compensate for each other, thus not significantly affecting the shape or position of the learning curve. The variations of more interest, discussed hereafter, are those which affect the height, linearity, or slope of the learning curve. These variations may be caused by external influences (e.g., Government directed engineering or schedule changes), or by factors inherent in the production process (e.g., the tendency of the curve component with the flattest slope to become the dominant component of the composite

curve at high cumulative production numbers). In order to be able to assess the predictability of learning curves, it is important to recognize the causes and impacts of various irregularities on the shape and position of those curves.

The irregularities referenced are generally attributed to engineering changes, follow-on production, variances in cost component significance, or discontinuities in resource application. The effect of most major engineering changes on a product already in production is that new work (varying in amount depending on the scope of the change) is added to the work in which some learning has already occurred. The learning theory applies to the new work as well as to the old; it is generally assumed that the learning curve for new work resulting from engineering changes has the same slope as the original curve. However, production of the new work is relatively inefficient initially, even though the rate of learning per unit is relatively great and improvement is rapid. Consequently, the effect graphically is to shift the learning curve vertically upwards (representing higher unit costs) by an amount determined by the complexity or impact of the change. Generally, this shifted curve is presumed to be asymptotically parallel to the original one, and not to intersect it. If a major change substantially alters the product complexity, production efficiency, or the mix of cost component contributions, it can result in a change in slope of the learning curve, usually also accompanied by a vertical shift proportional to the significance of the change. Minor engineering changes are also frequently introduced, either to improve production efficiency or product characteristics.

These changes tend to be offsetting and appear to have little observable effect on the learning curve slope or height.

Follow-on production is considered to occur when a significant time break interrupts the continuity of the production run, resulting in a loss of some amount of learning. A similar effect occurs when production of an established product is instituted in a new facility, and not all learning is effectively transferred. The direct labor curve tends to be flattened in its initial portion following such a disruption, but then resumes a downward slope parallel to (but above) the original curve.

Variances in the significance of the different cost components with increasing production quantities frequently result in some convexity (relative to the origin) of both the unit cost and the cumulative average cost curves at moderate cumulative production quantities. The amount of convexity appearing in the curves as a consequence of the linear components having different slopes varies with the degree of difference in the values of those slopes, and with the proportion of the total composite curve represented by each component curve. In general, the convexities in most curves have been found to be slight, and they are therefore disregarded for most purposes. It has also been noted that the direct labor curves for some products tend to flatten, or bottom-out, at high cumulative production quantities. This is most commonly explained as representing the fact that the slope of any composite curve will approach the slope of its component with the flattest slope at high cumulative production quantities (e.g., fabrication labor usually has a flatter slope than assembly labor).

Discontinuities in the application of resources also impact on the shape of learning curves. The cost of final units in a production series often turns sharply up or down. Upward trends (toe-ups) are considered to be a result of the transfer of experienced people to other jobs, and of increases in handwork as specialized tooling is withdrawn for other uses. Downward trends (toe-downs) are considered to be a result of the use of surplus materials (i.e., materials previously expensed). Unfortunately, these explanations do not permit accurate prediction of whether or when such turns will take place, or of their direction. However, since the overall costs associated with them are small compared with the cumulative total costs of the entire production, these turns do not warrant much attention.

All the perturbations just described complicate the interpretation of learning curves, since they can imply misleading conclusions, or in some cases mask the significant trends. The key factor to recognize is that every production learning curve is itself based on aggregation of lesser components, and consequently cannot be truly represented by simple mathematical expressions over very broad ranges. So long as this factor is recognized, and the effects of engineering changes and other production discontinuities are kept in mind, learning theory can indeed be a useful tool in a variety of applications, as previously summarized, within limits imposed by reliability and predictability considerations.

Reliability and Predictability of Learning Curves

A prime reason for fitting mathematical curves to learning theory has been to provide a technique for consistent and simple prediction

of values beyond the range of available data. In fact, most industry and Government uses of learning theory are principally concerned with its predictive capabilities. Short term predictions generally require greater accuracy than long term ones, and learning theory satisfies this requirement. Statistical measures are widely used to evaluate the accuracy and predictability of learning curves, as well as to establish empirical equations for developing generally applicable learning curves. However, several factors make application of statistical techniques to learning curves diffic [illegible]; in fact, failure to recognize and compensate for these factors often leads to misinterpretation of learning theory implications. For example, the implicit assumptions that components of cost per production unit are log-normally distributed and have constant variances within those distributions for all values of cumulative production quantities are, at best, broad assumptions to make. Large errors can result from the use of equations based on such assumptions when they do not really apply.

A further problem arises in trying to obtain a sufficient number of observations upon which to perform statistically significant regression analyses leading to identification of appropriate learning curve slopes. Clearly, the probability that the values of statistical measures are accurate is lowest when sample sizes are small. In practice, samples from other supposedly similar populations (i.e., similar products, either within the firm or the industry) are sometimes considered together with limited data from the population under study. Unfortunately, the use either of small sample sizes, or of samples swelled to adequate size by the inclusion of data which may

not be representative of the population being analyzed, can lead to erroneous and misleading conclusions.

It has also been recognized that transforming data logarithmically can have the effect of causing statistical measures to appear to be different (usually better, but sometimes worse) than they really are. Therefore, it must be realized that statistical measures based on logarithmic values of data may have different characteristics than they would if based on arithmetic values of the same data.

Autocorrelation is said to exist when the variations in observations in a time series are not independent of each other. Since the passage of time during the course of a production run permits the implementation of technological advances and management innovations, which seem to be significant contributors to the learning phenomenon, it is certainly likely that autocorrelation exists amongst learning theory observations. The existence of such autocorrelation may be expected to distort the values of statistical measures considered.

While statistical techniques can be used to evaluate extrapolated curves, there can be little if any mathematical certainty attached to the results. Statisticians vehemently recommend that curves should never be extrapolated beyond the range of the data, and that when they are so extrapolated (in spite of the preceding admonition), such extrapolation should be interpreted with the utmost caution. Nevertheless, forecasts and projections into the future being vital, learning theory has been developed and used extensively for such forward looking extrapolations.

In summary, the most important requirement in using learning curves as a tool for production cost estimating (or for any other purpose) is that the estimator be thoroughly familiar not only with learning theory, but also with all pertinent aspects of the particular industry to which he is applying learning theory. In common with most estimating tools and techniques, the potential for substantial errors is great. Consequently, the predictability and reliability of learning curves are, to a great extent, dependent upon the experience, knowledge, and judgment of the estimator who is applying them. This same note of caution is even more applicable when working with the extension of learning theory to the broader conceptual area known as the experience curve effect.

CHAPTER III — HISTORICAL DEVELOPMENT

The extensive review of learning curve and experience curve literature performed in preparation for the present research is documented in this chapter. Significant prior work is discussed, and attention is directed to some of those areas which have been relatively neglected or otherwise incompletely treated in prior research. Emphasized in particular are the relationship of prices to costs, the effects of alternative inflation treatments, the handling of implicit prior experience, the development of variants of the traditional power form learning model, and the variability of experience curve slopes. Through tracing the historical development of both learning and experience curves, the foundations of the experience curve effect are more clearly established. The first few pages of this chapter provide a perspective on the nature of the literature. Most of the chapter, however, is devoted to elaborating on those aspects of previous work which contributed to formulation of the present research effort.

Chronological Literature Content Matrix

Sixty-four treatises, considered to be representative of publications relating to the development of learning and experience theory in the context of industrial manufacturing operations from 1936 through 1976, are summarized in chronological sequence in Table 2. Each

TABLE 2 — CHRONOLOGICAL LITERATURE CONTENT MATRIX

REFERENCE	NATURE OF TREATISE: Government Report	Journal Article	Master's Thesis	PhD Dissertation	Text or Book	OBJECTIVES: Develop New Ideas	Examine Empirical Data	Motivate Applications	Provide Learning Tables	Review History	MODELS: Comparisons of Theories	Cumulative Average Theory	Level of Aggregation	Log-Linearity of Relations	Other Theories	Representative Slopes	Slope-Intercept Correlation	Unit Theory	VARIABLES: Implicit Prior Experience	Inflation Adjustments	Lot Midpoint Determination	Prices as Cost Surrogates	Production Parameters	Technical Performance	CONCEPTS: Competitive Effects	Factors of Learning	Learning Curve Hazards	Production Discontinuities	Strategic Implications	Uses of Learning Theory
Wright, 1936		X				X	X	X				X	X	X		X						X				X		X		X
Gibson, 1949				X		X	X									X		X	X				X			X		X		X
Andress, 1954		X						X				X				X										X				X
Asher, 1956				X		X	X		X	X	X	X	X	X	X	X	X	X		X						X			X	X
Baguero, 1957	X							X		X	X					X		X	X				X			X	X	X		X
Conway & Schultz, 1959		X					X	X			X	X	X			X		X					X			X	X			X
Lenke & Edwards, 1961					X			X				X														X				X
Jones, 1962	X							X	X									X			X					X				X
Baloff, 1963				X		X	X								X		X						X			X		X		X
Hirschmann, 1964		X					X	X										X				X				X	X			X
Keachie, 1964	X						X	X			X	X	X	X	X	X	X	X					X			X	X		X	X
Scherer, 1964					X		X	X				X				X	X								X	X				X
Harris et al, 1965	X							X	X	X	X	X						X			X					X		X		X
Brewer, 1965			X					X			X	X		X				X			X					X	X	X		X
Kelley, 1965	X							X										X												X
Anthony, 1965					X			X				X	X													X				X
Baloff, 1966		X						X							X								X			X				X
Arditti, 1967	X					X												X					X		X	X			X	X
Colasuonno, 1967			X							X			X		X								X			X	X			X
Dahlhaus & Roj, 1967	X							X							X						X					X				
Brockman & Dickens, 1967			X				X				X	X			X		X	X						X		X				X
Hoffmann, 1968		X				X						X						X	X								X			

TABLE 2 — cont.

REFERENCE	NATURE OF TREATISE					OBJECTIVES					MODELS								VARIABLES						CONCEPTS					
	Government Report	Journal Article	Master's Thesis	PhD Dissertation	Text or Book	Develop New Ideas	Examine Empirical Data	Motivate Applications	Provide Learning Tables	Review History	Comparisons of Theories	Cumulative Average Theory	Level of Aggregation	Log-Linearity of Relations	Other Theories	Representative Slopes	Slope-Intercept Correlation	Unit Theory	Implicit Prior Experience	Inflation Adjustments	Lot Midpoint Determination	Prices as Cost Surrogates	Production Parameters	Technical Performance	Competitive Effects	Factors of Learning	Learning Curve Hazards	Production Discontinuities	Strategic Implications	Uses of Learning Theory
James, 1968		X				X									X									X				X		
Schumacker, 1968				X		X	X								X			X					X	X		X				
Kiefer, 1969	X					X			X			X			X															X
Barrett, 1969				X		X	X					X	X	X	X	X										X	X			X
Hartung, 1969	X							X			X	X			X			X	X								X			
Booz-Allen, 1969	X					X	X								X		X			X				X	X					
Batchelder et al, 1969	X							X			X	X			X			X			X			X		X	X			X
Conrad, 1969				X		X	X					X			X											X		X		X
Hartung, 1970	X							X				X						X	X		X					X	X	X		X
Orsini, 1970			X							X		X			X			X					X			X	X	X		X
Boren & Campbell, 1970	X								X			X						X			X						X			
Conley, 1970		X						X				X	X					X		X		X				X	X		X	X
Ilderton, 1970			X					X			X	X			X	X		X			X					X	X			X
Anthony, 1970					X			X				X														X				X
Gossett, 1971	X							X										X					X		X			X		X
Karsch, 1971	X							X				X			X			X									X			
Waggoner, 1971	X						X	X								X				X	X	X	X			X				
Morse, 1971				X		X									X															X
Boston Consulting Group, 1972					X	X	X	X				X	X			X				X		X			X	X	X	X	X	X
Woolley, 1972				X		X	X					X	X			X				X		X				X	X		X	X
Puryear, 1972	X							X							X								X				X			X
Kotler, 1972					X			X				X														X			X	

TABLE 2 — cont.

	NATURE OF TREATISE					OBJECTIVES					MODELS								VARIABLES						CONCEPTS					
REFERENCE	Government Report	Journal Article	Master's Thesis	PhD Dissertation	Text or Book	Develop New Ideas	Examine Empirical Data	Motivate Applications	Provide Learning Tables	Review History	Comparisons of Theories	Cumulative Average Theory	Level of Aggregation	Log-Linearity of Relations	Other Theories	Representative Slopes	Slope-Intercept Correlation	Unit Theory	Implicit Prior Experience	Inflation Adjustments	Lot Midpoint Determination	Prices as Cost Surrogates	Production Parameters	Technical Performance	Competitive Effects	Factors of Learning	Learning Curve Hazards	Production Discontinuities	Strategic Implications	Uses of Learning Theory
Wortham & Misra, 1972		X						X			X	X						X									X			
Puryear, 1973	X					X									X												X			
Fasio & Russell, 1974			X			X									X			X		X			X			X				
Bernard, 1974		X						X			X	X			X			X	X								X			
Pichon & Richardson, 1974			X			X									X								X					X		
Abernathy & Wayne, 1974		X						X				X											X				X		X	
Daniels, 1974	X					X									X					X			X	X						X
Large et al, 1974	X						X						X		X	X	X						X	X						X
Malstrom, 1974				X		X	X						X		X															
Riebel, 1974					X			X				X				X			X											X
Tilles, 1974					X			X				X										X							X	
Jain, 1975		X						X				X	X									X							X	
Carlson, 1975		X				X						X			X								X							X
Burns, 1976	X							X			X	X			X	X		X			X		X			X	X	X		X
Abernathy, 1976					X	X						X						X					X	X		X			X	
Fisher, 1976	X							X				X						X									X			X
Buck et al, 1976		X				X		X			X	X			X			X									X			
Smith, 1976				X		X	X						X		X			X					X					X		X
Carlson & Rowe, 1976		X				X						X			X			X					X							X
Pegels, 1976		X				X						X			X															X
COLUMN ENTRY TOTALS:	22	16	7	10	9	26	19	36	5	5	14	40	14	5	33	16	7	32	7	8	10	8	23	8	5	36	26	15	11	43

treatise in Table 2 is referenced by author and by year of publication; full citations for each are contained in the Bibliography. Major column headings in the matrix are Nature of Treatise, Objectives, Models, Variables, and Concepts. Each of these topics will be expanded upon in subsequent sections of this chapter. It should be noted that the objective of this chapter is not to reiterate in detail all prior work in the areas of learning and experience. Rather, it is to draw attention to and to emphasize those areas which have been relatively neglected in prior research, with particular emphasis on the research opportunities selected for investigation in the course of the present research, as reported in the following chapters.

Before proceeding with elaboration of the literature content matrix, a few treatises of particular merit should be singled out. The first documentation of what came to be known as learning curve theory was in the form of a 1936 article by T. P. Wright, a vice-president and General Manager of the Buffalo division of the Curtiss-Wright Corporation. His article documented his findings from cost-quantity studies initiated in 1922. The article is particularly noteworthy not only because it was the first, but also because most of his insights and interpretations remain valid even now, more than half a century after his studies commenced.

Harold Asher's 1956 PhD dissertation, prepared at Ohio State University and later also published by The RAND Corporation, provides the most comprehensive look at the state of the art of learning theory after twenty years of development. Asher's work also reflects the first recognition of the strategic concept which much later became the

core idea of experience curve theory: "Manufacturers who have been producing a given type of product for a long time have a distinct advantage over newcomers in the industry. . . . With luck, and with sufficient financial backing, the newcomer may reach a cumulative output that will put him within reach of his competitor's production costs" (Asher, 1956, p. 139).

Nicholas Baloff's 1963 PhD dissertation, prepared at Stanford University, demonstrated that the theory of learning was applicable to capital intensive industry as well, and not only to labor intensive industry as previously believed. His work was also particularly useful in that it showed the applicability of learning theory in the steel, glass, and paper industries, as distinct from the aircraft industry which had been the focal area of most of the research up to then.

Working under a Small Business Administration grant, E. C. Keachie of the University of California at Berkeley investigated the potential strategic benefits of learning theory for sixty small business firms. In the findings he reported in 1964, he also demonstrated substantial strategic insight: "The first producer in a field is already 'down the curve' on his costs when newcomers begin, so they can expect comparable costs only after comparable cumulative production, other things being equal" (Keachie, 1964, p. 44).

The reader who is seeking a textbook approach to the field of learning theory has two complementary options, both prepared in 1965. The Government report prepared by Robert Harris and other personnel of the U.S. Army Missile Command's Redstone Arsenal emphasizes the

mechanics of learning curve computations, the use of published learning factors tables, and the use of time-shared computer programs. It is clearly oriented towards the practitioner who must become adept with learning curve manipulations. The Master of Science thesis written by Glenn Brewer of the Air Force Institute of Technology takes a more formal approach to the subject of learning theory, emphasizing those considerations of particular concern to managers or decision makers responsible for interpreting the implications and applying the projections of learning curves.

The reader who is seeking a comprehensive review of developments affecting the field of learning theory should review two Master of Science theses, both written by students of the Air Force Institute of Technology. The 1967 work of Vincent Colasuonno concentrates on the decade from 1956 to 1966; the 1970 work of Joseph Orsini extends that review to 1970.

Finally, the reader seeking a fuller understanding of the broader concept of experience curve theory, as outlined in Chapter I, again has two complementary options. The book Perspectives on Experience, written by the staff of The Boston Consulting Group in 1968 (and reprinted in 1970 and 1972), describes in detail the experience curve effect and its strategic implications. That work is corroborated by Kenneth Woolley's 1972 PhD dissertation, prepared at Stanford University. He aptly summarizes the strategic nature of experience curve theory: "The concept of the experience curve is essentially that of the total firm as a *system, innovating,* adapting to technological change, and reacting to the pressure to reduce costs" (Woolley, 1972, pp. 46-47).

Nature of Treatise

The nature of each treatise is identified in Table 2 by placement into one of five categories: Government Report, Journal Article, Master's Thesis, PhD Dissertaiton, or Text or Book. (Copies of some of the dissertations, theses, and articles are also available as Government reports; this information is reflected in the Bibliography, but not in Table 2.) The ten dissertations listed are the only ones identified as relevant to learning and experience theory in the context of industrial manufacturing operations. In each of the other four categories, however, the treatises listed constitute only a representative sample, not the total population. Amongst the texts and books cited, only the 1972 book by The Boston Consulting Group is devoted to the subject of experience curve theory; each of the others mentions learning or experience theory in passing, rather than focusing on that subject.

Inferred Objectives

The main objectives of each treatise, as inferred from the review, are identified in the matrix of Table 2 as being to: Develop New Ideas, Examine Empirical Data, Motivate Applications, Provide Learning Tables, or Review History. Forty-two of the treatises appeared to have a single dominant objective, while only one (Asher, 1956) was considered to have as many as four. The commonest objective observed was motivation of further applications of the theory (56% of treatises),

followed by development of new ideas (41%) and examination of empirical data (30%).

It is interesting to note that even in the early 1960's, a quarter of a century after Wright first published results of his studies of cost-quantity relationships, some motivational statements were still couched in cautious terms. For example: "There is every indication that the learning curve offers a practicable answer to the needs of thousands of manufacturing companies for fairly accurate forecasts of direct labor requirements and productivity, but it is still a new device in a more or less experimental stage" (Lemke and Edwards, 1961, p. 168). Fortunately, not all authors were so reserved: "The learning curve, I believe, is an underlying natural characteristic of organized activity, just as the bell-shaped curve is an accurate depiction of normal, random distribution of anything, from human IQ's to the size of tomatoes" (Hirschmann, 1964, p. 125).

The objective of providing comprehensive learning tables has been adequately satisfied by the three volume 1970 work of Boren and Campbell of The RAND Corporation. For slopes from 55% Through 99%, and for both the long-linear cumulative average and the log-linear unit learning theories, their tables provide lot midpoints, cumulative total factors, cumulative average factors, and unit factors, for lot sizes from 1 through 2000 units. (These factors can be readily transformed to represent costs, prices, hours, or other parameters.) Special purpose tables prepared by Kiefer in 1969 are also noteworthy, since they relate degree of completion to extent of expenditures for acquisition

programs with slopes from 51% through 99%. Kiefer's tables are based on the log-linear cumulative average learning theory.

Models Considered

Under the general heading of Models, Table 2 reflects the content of each treatise reviewed in terms of eight topics: Comparisons of Theories, Cumulative Average Theory, Level of Aggregation, Log-Linearity of Relations, Other Theories (i.e., other than Cumulative Average and Unit Theories), Representative Slopes, Slope-Intercept Correlation, and Unit Theory. Both the cumulative average theory and the unit theory have been adequately reviewed in Chapter II. Each of the other six topics will be addressed further in the balance of this section, with emphasis given to work which leads into the present research.

Comparisons of Theories

Comparisons of theories were made in 22% of the treatises reviewed; these comparisons in most instances consisted of subjective expositions of merits and faults. In practically all cases, these comparisons were made between the cumulative average and the unit theories. All of these comparisons are in essence the same. Conway and Schultz (1959) suggest that, since unit curves and cumulative average unit curves are asymptotically parallel, the choice between them is largely a matter of convenience. They caution, however, that the smoothing effect of averaging (in the cumulative average theory) may conceal significant short term perturbations. Similarly, "Since the cumulative average curve smooths and flattens the slope and thus facilitates cost estimating, the unit curve shows up variations better

for analysis and control of productivity" (Keachie, 1964, p. 43). Harris et al. (1969) reiterate the above views, and also point out the practical consideration that data are much more readily available and more easily manipulated (since there is no concern over locating lot midpoints) for cumulative average theory than for unit theory.

Hartung (1969) demonstrates that using cumulative average theory when in fact unit theory is more appropriate will always result in underestimating costs (note the relative positions of the curves in Figure 3 of Chapter II). Conversely, he also shows that using unit theory when in fact cumulative average theory is more appropriate will always result in overestimating costs. (The implication here is that unit theory should be used whenever there is doubt as to which is appropriate, thus avoiding underestimates.) In view of the asymptotic nature of the curves resulting from the two theories, Ilderton (1970, p. 3) concludes that, for purposes of forecasting, the choice between them ". . . is virtually meaningless in industries which produce large quantities of comparatively low cost items."

For purposes of the present research, both theories will be tested, but the greater emphasis will be placed on the cumulative average theory.

Level of Aggregation

The issue of level of aggregation (ranging from direct costs through total manufacturing costs to market prices) was also addressed in 22% of the treatises reviewed. Wright (1936) examined cost-quantity relationships at the levels of direct labor, raw material, purchased

material, and the whole airplane. He noted that the increasing importance of material over labor at higher cumulative production quantities caused the whole airplane cost slope to change with quantity. Conway and Schultz (1959, p. 44) reported that "In the several situations in which the authors have considered different levels of the same product, it has been uniformly true that the variability of the data varied inversely as the level of aggregation." They also expressed the view that errors resulting from aggregation would only become significant with extreme extrapolation. Similarly, "The variability of progress curves diminishes as one aggregates groups of operations" (Keachie, 1964, p. 42). Stated another way, "There is the possibility that the total cost curve slope may not be as dependent on component curve slopes as has been generally thought, because of the characteristics of regression fitting of data points" (Colasuonno, 1967, p. 18).

Anthony (1965) suggests that not all costs decrease, and that of those which do decrease, not all do so at the same rate; consequently, individual costs should be projected at their respective learning rates, and the results summed. Conley (1970) likewise points out that if the individual cost elements of a project follow different learning curves, then the total cost can only be approximated by a composite log-linear curve. Disagreeing with Anthony, and accepting the possibility of error inherent in a further approximation, Jain (1975, p. 29) states that all costs decrease as experience increases, and in fact that "Decline in all costs is the cardinal tenet of the experience concept."

For purposes of the present research, four levels of aggregation will be investigated. At the lowest level, curves will be determined for both direct labor costs and purchased material costs. At an intermediate level, total manufacturing costs will be assessed. At a higher level, market prices for a sub-industry (as opposed to individual firms) will be analyzed.

Log-Linearity of Relations

The question of log-linearity of relations (i.e., whether or not empirical data truly conform to the logarithmically transformed power form model) was first raised by Wright (1936), but has been seriously addressed in only 8% of the treatises reviewed. It is no longer considered to be an important issue. It is generally recognized that learning curves are only approximations, and thus should not be expected to be truly log-linear when fitted to actual data. There are, of course, continuing efforts to identify better cost estimating relationships. As stated by Asher (1956, p. v), "It is clearly a matter of judgment whether or not the linear curve is appropriate in a specific case." In Barrett's 1969 PhD dissertation, he emphasizes that the simplicity of the log-linear assumption is the prime motivator for its widespread use. In his research, he found that in general "There is at least one non-linear form which gives a significantly better fit than the linear form" (Barrett, 1969, p. 60). He further recognized that "There is a tradeoff of cost of simplicity for cost of accuracy if one accepts the non-linearity hypothesis and each firm must weigh these costs for itself" (Barrett, 1969, p. 99).

For purposes of the present research, log-linearity (or its absence) will be used only as an indicator of when a more complex model, or a piece-wise log-linear model, should be examined.

Other Theories

Other theories than the traditional power form models (i.e., the Cumulative Average Theory of Wright and the Unit Theory of Crawford) have been advanced in fully 52% of the treatises reviewed. Attention will be drawn here only to those authors whose work influenced the design of the present research effort. In advocating the explicit consideration of production parameters when analyzing costs, Keachie (1964, p. 43) states "To reduce costs by effective industrial engineering and management techniques it is usually mandatory to work with curves that are truly representative of the progress taking place on the specific operations concerned, both to show up where greater improvement can be expected, and to help point up ways it can be accomplished." Similarly, "Preoccupation with expected log-linear reductions may mask opportunities for greater reductions" (Colasuonno, 1967, p. 84).

Brockman and Dickens (1967) experimented with multiplicative predictive models of the form

$$Y = C\,X_1^D\,X_2^E \tag{11}$$

However, the independent variables in their cost estimating relationships represented physical characteristics of the products, not cumulative quantities or production parameters. Further, they acknowledged that "The use of this multiplicative, exponential form

for predictive equations employing more than one independent variable is justified more on the grounds of accepted convention and practicality than by any theoretical justification" (Brockman and Dickens, 1967, pp. 67, 68). Schumacker (1968) sought to explain deviations from learning curve cost projections in terms of production related variables such as production experience, rework, parts-not-available, and experience of the work force; he found the last of these variables to be the most significant. Orsini (1970) mentions experimenting with a predictive model of the form of equation (11), but with the independent variables representing cumulative production quantity and production rate; he does not detail the results obtained.

Ilderton supports the idea of more complex models: "In the opinion of the author, the most promising area for further improvement in the use of historical data to predict labor hour requirements lies in the development of computer programs to fit data to models which consider more factors than just the number of units produced" (Ilderton, 1970, p. 71). Large et al. (1974) report applying the model of equation (11) in the manner reported by Orsini to seven aircraft programs, but obtaining higher coefficients of determination when the production rate factor was omitted. They trace the origin of that model to Levenson, also of The RAND Corporation, who reportedly experimented with a model of the form

$$T = B_0 \, X_1^{B_1} \, X_2^{B_2} \, X_3^{B_3} \, X_4^{B_4} \qquad (12)$$

in which the dependent variable was total tooling hours and the independent variables represented cumulative production quantity, production rate, and aircraft technical parameters (weight and speed).

Buck et al. (1976) investigated a discrete exponential model as an alternative to the traditional power form model. They were motivated by the consideration that "The wide variety of learning applications stretch from organizational to individual operator phenomena where different learning causes are expected to create different behaviors in the learning effects. To empirically capture this diversity for accurate forecasting, one must have a variety of learning curve models and sound methods of parameter estimation for each" (Buck et al., 1976, p. 193).

Smith (1976) investigated a model of the form of equation (11), with the dependent variable representing fabrication hours per pound, the first independent variable representing cumulative production, and the other independent variable representing alternatively lot average monthly manufacturing or delivery rate. Smith believed that unit curve theory best applied for the learning parameters, and hence he used algebraic lot midpoints in valuing the cumulative production variable.

Finally, Carlson and Rowe (1976) proposed that learning loss, or forgetting, can be handled as a log-linear curve of performance reduction over equivalent units which would have been produced had production not been interrupted. In other words, performance loss may be viewed as a function of the performance level when learning was interrupted and of the duration of the interruption.

For purposes of the present research, it was determined that a model of the general form of equation (12) offered interesting potential for effectively combining the apparently dominant effect of

cumulative production quantity with the relatively small but still conceivably important effects of additional factors influencing product costs and prices. As will be shown in Chapter IV, this model is theoretically and intuitively appealing, yet simple enough to encourage widespread applications.

Representative Slopes

Representative slopes for learning or experience curves were included in 25% of the treatises reviewed. Based on his initial studies, Wright (1936) suggested the following slope factors as apparently representative for aircraft manufacturing: Direct Labor, 80%; Purchased Material, 88%; Raw Material, 95%; Overhead, 70%; Total Cost, 83% to 90% (dependent on quantity). Reviews of data based on World War II aircraft production (e.g., Gibson, 1949; Asher, 1956) showed that, while Wright's values might indeed have been representative of his data, they were by no means unchangeable. Recognizing that there are significant differences in patterns of progress for different industries, firms, products, and types of work, Conway and Schultz (1959, p. 53) stated: "No particular slope is universal, and probably there is not even a common model."

Nevertheless, Keachie in 1964 proposed what he considered to be representative direct labor slopes for small manufacturing businesses: Fabrication, 90%; Assembly, 75%. Similarly, Scherer in 1964 reported that two major aerospace firms competitively producing the same type of air-to-air guided missile were both experiencing about a 76% overall direct labor slope. He also recognized, however, that

efficiency must be judged on a combination of slope and imputed first unit intercept value, since steep curves could reflect early inefficiency rather than sustained efficiency.

The extent of the variation in learning curve slopes from one product to another and from one account (i.e., labor cost, material cost, overhead cost, total cost) to another is suggested in Table 3. The figures given are the slopes determined by Barrett (1969) using regression techniques on empirical data in the course of his PhD research. In spite of the variations in slope from one product to another, many authors continue to report only "industry average" slope factors. For example, Ilderton (1970) cites a 1968 study conducted by the Defense Contract Audit Agency which showed the mean and median slopes for direct labor costs for 204 aerospace industry contracts to be 84.9% and 85.0%, respectively.

TABLE 3 - SLOPE VARIATIONS BY PRODUCT AND ACCOUNT

Account	Product		
	Engine A	Computer A	Computer Z
Labor Cost	87.51	77.64	90.11
Material Cost	91.53	86.30	87.49
Overhead Cost	96.39	-	-
Total Cost	91.38	82.13	88.64

Source: Barrett, 1969, pp. 50, 74, 75.

Waggoner provided considerably more useful information in a 1971 Government report. He reported not only average slopes, but also standard deviations and extreme values, broken out by sub-industry category, for a wide variety of U.S. Army procurements, including electronics procurements managed by the Army Electronics Command. These values are of particular interest for two reasons: first, they are based on the prices paid by the Army for the various items of equipment, rather than being based on some level of accounting costs; second, the sub-industry categories provide a baseline for comparison with the results of the present research into avionics experience curve behavior. In some instances, Waggoner found a "negative learning" effect, reflected by slope values greater than 100%. He attributed these unusual slopes to inflationary effects (since no inflation adjustments were made in the cases he reviewed), production discontinuities such as design changes, uneconomical production rates, and wearing out of production facilities. Representative results, useful for later subjective comparisons with the results of the present research, are presented in Table 4.

The Boston Consulting Group (1972) treatise includes many graphs reflecting experience patterns in the electronics, petrochemicals, consumer hardgoods, and consumer softgoods industries. Typically, the slopes shown range from 60% to 90%, usually based on prices rather than costs, and inflation adjusted. In most examples, the empirical data points have been fitted with two or three log-linear segments, rather than by a single constant-sloped curve. Woolley (1972) examined additional inflation-adjusted price data, primarily

TABLE 4 — REPRESENTATIVE ELECTRONICS EXPERIENCE SLOPES

Category	No. of Items	Low Value	High Value	Mean Value	Std. Deviation
Radio Equipment (A)	37	61.7	100.0	94.4	7.29
Radio Equipment (B)	37	61.7	122.0	95.6	9.07
Transponders (A&B)	9	70.7	100.0	93.3	9.52
Navigation Systems (A)	4	90.2	100.0	95.8	5.00
Navigation Systems (B)	4	90.2	112.0	98.8	9.74
All Electronics (A)	162	61.7	100.0	95.6	6.11
All Electronics (B)	162	61.7	130.0	97.0	8.25

(A) — Slope values greater than 100% truncated to 100%.

(B) — Slope values as experienced, without truncation.

Source: Waggoner, 1971, pp. 22, 25.

from the same industries as reported by The Boston Consulting Group, and found slope values ranging from 44.4% (theoretically impossible with cumulative average theory, but not explained by Woolley) to 92.5%, but mostly clustered between 73% and 85%, with a median value of 77.5%.

Other authors continue to cite what they consider to be broadly representative slopes, in spite of the questionable value of such factors. Large et al. (1974) suggest that the purchased material learning curve in the aircraft industry averages about 89%. Niebel (1974) suggests that assembly labor typically will conform to a slope of from 70% to 80%; he further proposes separate ranges for different aspects of fabrication, with welding expected to fall between 80% and 90%, and machining between 90% and 95%.

Although not recommending specific slope values as representative, Harris et al. (1965) suggest an order of desirability for approximating an unknown slope (i.e., when there is no directly applicable experience base for determining a contractor's slope on a specific item). They recommend, in essence, six alternatives, listed from most desirable to least desirable:

1. Use the same contractor's slope for similar items, or
2. Use the same contractor's average slope, or
3. Use an industry average slope for the same item, or
4. Use another contractor's slope for the same item, or
5. Use an industry average slope for similar items, or
6. Use another contractor's slope for similar items.

For purposes of the present research, it will be of interest to see how avionics procurement slopes compare with the various

representative slopes cited in this section. While it would also be of interest to see if the rank ordering suggested by Harris _et al_. for the relative desirability of slope approximation alternatives can be either rejected or supported, data limitations unfortunately preclude a formal analysis.

Slope-Intercept Correlation

Some commentary as to the nature or degree of correlation between learning curve slope and imputed first unit cost intercept was found in 11% of the treatises reviewed. Asher (1956, p. 78) investigated the possibility of a relationship between slope and intercept (_a_ value), concluding: "However, whether slope or _a_ value is considered the independent variable, there is little doubt that these two variables are related to one another." He found that the intercept value tended to be higher and the slope steeper when new fighter aircraft models were substantially different from models previously produced at a contractor's facility. The intercept tended to be lower and the slope flatter when successive models were more similar. Baloff (1963) found confirmation of Asher's observed aircraft industry relationships in the parameters associated with new product manufacturing start-ups in the steel, glass, paper, and electrical industries.

Keachie (1964) found that most small business firms appeared to do too little preplanning, typically evidenced by steep learning slopes. Whereas a shallow slope could imply inefficiency in learning, it could also imply excessive perfectionism in preplanning, with the attendant penalties of delayed market entry with a new product. Recognizing that

"The more a situation requires in-production attention and change, the steeper the progress curve becomes," Keachie (1964, p. 17) advocates the importance of seeking an optimum balance between preplanning and learning after production starts. The immediate costs of preplanning activities must be weighed against the anticipated costs of production inefficiencies.

For purposes of the present research, the question of slope-intercept correlation is not being investigated; it is considered sufficient to recognize that they are interdependent variables.

Variables Considered

Under the general heading of Variables, Table 2 reflects the content of each treatise reviewed in terms of six topics: Implicit Prior Experience, Inflation Adjustments, Lot Midpoint Determination, Prices as Cost Surrogates, Production Parameters, and Technical Performance. Each of these six topics will be addressed further in the balance of this section, with emphasis again given to work which leads into the present research.

Implicit Prior Experience

The effect of prior experience with identical or similar products on the learning phenomenon and on learning curve parameters has been addressed in only 11% of the treatises reviewed. Gibson (1949) found that, in the early phases of a new model production, progress curve steepness seemed to be controlled largely by prior experience within the production facility. As reported by Reguero (1957) and others, the Stanford Research Institute in 1949 proposed recognition of prior

experience by incorporation of an added factor into the traditional form of the learning curve equation:

$$Y = A\ (X + C)^{B} \tag{13}$$

In this formulation, B was generally assumed to equal -0.5, corresponding to a fixed slope of 70.7%, and C was assigned various values until a "best fit" regression equation was obtained. Based on analysis of World War II aircraft production data, the Stanford researchers arrived at C values ranging from -3.0 to +179.2 (Hartung, 1969). The value of C, representing implicit prior experience, served to adjust the curve slope at low production quantities, but had little effect at high quantities. The Stanford formulation has been used relatively infrequently, since "There are only a few samples of learning curve data that can be better described by the Stanford equation instead of by the straight line on log-log paper" (Reguero, 1957, p. 219).

Hoffman (1968) derived mathematical expressions and representative curves showing that the true slope is steeper than the observed slope when prior experience is not properly accounted for. He related true slope to observed slope by the equation:

$$\frac{\log S_T}{\log S_0} = \frac{\log X_0}{\log\ [(X_0 + C)/(1 + C)]} \tag{14}$$

where S_T = True Slope, S_0 = Observed Slope, X_0 = Observed Cumulative Quantity, and C = Prior Experience Quantity. (If the true slope is known in some way, expression (14) can instead be solved for the variable C, yielding a value for implicit prior experience.) It is significant to note that the slope relationship is dependent only on quantities, not on costs.

For purposes of the present research, a variant of the Stanford equation, to be defined in Chapter IV, will be investigated.

Inflation Adjustments

The subject of inflation adjustments was addressed in 13% of the treatises reviewed. Asher (1956) suggested the use of price indices to compensate for inflation effects. Booz-Allen (1969) reported adjusting cost data to constant dollars using special price indices provided by the Army Electronics Command. Conley (1970) and The Boston Consulting Group (1972) advocate use of implicit price deflators based on the Gross National Product. Waggoner (1971, p. 46) comments that "Inflation appears to have a more significant effect on the slope as slope nears 100%. In addition, as the average quantity buy becomes smaller, and as the number of procurement years become larger, the slope is affected more and more significantly." The importance of recognizing inflationary effects is beginning to be acknowledged in recent work. For instance, "The underestimation of inflation historically has been a major contributor to cost growth in advanced acquisition programs and is now a concern of major proportions to on-going programs" (Fazio and Russell, 1974, p. 37). However, little if anything has been done to compare and contrast different methods of compensating for inflation effects in learning models.

For purposes of the present research, the effects of alternative treatments of inflation will be investigated.

Lot Midpoint Determination

Lot midpoint determination has been discussed in 16% of the treatises reviewed. (Recall from Chapter II that the algebraic lot midpoint is the unit number which represents the average unit cost of the lot.) Jones (1962) pointed out that, under the unit theory, arithmetic lot midpoints are only approximations, and algebraic midpoints would be more correct. He provided tables of such midpoints, computed by an iterative technique. Brewer (1965) suggested two alternative simple rules for determining approximate lot midpoints, but with no indication of choice criteria. As one rule, he proposed multiplying the first lot size by 0.3 and adding 0.5, and using arithmetic lot midpoints for all other lots. Alternatively, he proposed dividing the first lot size by 3.0 if the lot size does not exceed 10, and using the arithmetic midpoint for the first lot as well as later lots otherwise. Dahlhaus and Roj (1967) suggest that the "one-third rule" should be applied for first lots of up to 50 units; they also comment to the effect that, while algebraic lot midpoints offer some refinement, they are generally unnecessarily complicated. Batchelder _et al_. (1969) feel that non-arithmetic midpoints are likely to be important only for first lots of 25 or fewer units. (These suggestions and feelings were based on empirical knowledge of those authors.)

Waggoner (1971) proposes an iterative technique, similar to that of Jones, for lot midpoint determination. He suggests starting with an approximate or estimated B value, determining adjusted lot midpoints, finding a new B value from regression using those adjusted midpoints,

and repeating until the change in B value becomes insignificant. His formula is

$$K = \{N(B + 1)/[(L + .5)^{B+1} - (F - .5)^{B+1}]\}^{-1/B} \quad (15)$$

where K represents the algebraic lot midpoint, N represents the number of units in the lot, L represents the cumulative number of the last unit in the lot, F represents the cumulative number of the first unit in the lot, and B represents the slope (learning rate) parameter.

For purposes of the present research, arithmetic midpoints have been used exclusively, since the refinement resulting from determination of algebraic midpoints appears to be trivial.

Prices as Cost Surrogates

Prices have been widely used as cost surrogates, although only 13% of the treatises reviewed discuss this substitution. In his original work, Wright (1936) advocated applying his learning curve theory to negotiated prices of vendor items, as an aid in projecting "should cost" estimates. Many firms follow Wright's recommendation in dealing with their suppliers (Hirschmann, 1964). The broader strategic implications of considering price to closely follow cost in competitive markets, as reflected in price-volume experience curves, were not brought out until relatively recently (e.g., Conley, 1970; Boston Consulting Group, 1972; Tilles, 1974). The extensive data on learning slopes realized by the Army, as reported by Waggoner (1971), were all based on prices paid by the Army, rather than on accounting costs at some lower level of aggregation. These slopes might thus more properly be referred to as experience slopes.

In his PhD dissertation, Woolley (1972, p. 25) states: "Friedman claims that the best measure of average cost is price." This attribution may be just rationalization of the lack of good cost data. However, Woolley (1972, p. 61) goes on to explain: "The more competitive the market, the more quickly prices change in response to changes in demand. Over long periods of time and if there are no specialized factors of production, excess profits are eliminated, and even administered prices will change to reflect underlying cost changes within the industry." Finally, he summarizes the advantages and disadvantages of using prices as cost surrogates, indicating ready availability of data and market allocation of joint costs as the principal advantages, to be weighed against the disadvantages of possible collusion amongst sellers and concealed effects of demand shifts.

For purposes of the present research, strong emphasis will be placed on the use of price data, although some comparisons with various levels of aggregation of costs will also be made.

Production Parameters

Although 36% of the treatises reviewed recommend consideration of various production parameters (e.g., production rate, production break duration, delivery lead time, production lot size) together with cumulative production in arriving at cost or price projections, there is relatively little agreement as to which specific parameters to consider or how to incorporate them into a practical model. Those production related parameters considered in two or more of the treatises reviewed are identified in Table 5.

TABLE 5 — PRODUCTION PARAMETERS CONSIDERED

Reference	Delivery Lead Time	Experience of Work Force	Number Final Assembly Areas	Number Work Shifts	Prod. Break Duration	Production Experience	Prod. Facility Wearout	Production Lot Size	Production Rate	Prod. Run Duration
Gibson, 1949									X	
Conway & Schultz, 1959	X								X	X
Baloff, 1963, 1966									X	
Keachie, 1964	X									
Arditti, 1967									X	
Colasuonno, 1967	X								X	
Schumacker, 1968		X				X				
Orsini, 1970									X	
Gossett, 1971					X					
Waggoner, 1971							X		X	
Puryear, 1972								X	X	X
Fazio & Russell, 1974			X	X					X	
Pichon & Richardson, 1974					X			X		
Daniels, 1974					X				X	
Large *et al*., 1974	X	X	X	X		X	X	X	X	X
Carlson, 1975								X		
Burns, 1976					X					
Smith, 1976									X	
Carlson & Rowe, 1976					X					
Totals:	4	2	2	2	5	2	2	4	12	3

The greatest attention was paid to production rate. Orsini (1970) experimented with production rate as an added variable in both additive and multiplicative variations of the traditional power form learning model, and reported statistically better results than with the basic traditional model. Fazic and Russell (1974), working with peak production rates, found that 1) Rate tooling (i.e., tooling required to support higher production rates than initial tooling), sustaining tooling (i.e., continuing tooling maintenance and replacement), and rate equipment costs (per unit produced) all increase with production rate, 2) Manufacturing material, quality control, sustaining engineering (i.e., continuing production support engineering), and overhead costs all decrease as production rate increases, 3) Initial tooling costs are insensitive to production rate, and 4) Total manufacturing costs are not predictable as a function of production rate. Similarly, Large _et al_. (1974) found that the influence of production rate on cost cannot be predicted with confidence, but rather each case must be examined individually. They attribute this in part to the fact that "Decisions on rate of output are based on military, financial, and political considerations, not efficiency of production" (Large _et al_., 1974, p. 8). However, Smith (1976) found that a cumulative production and production rate multiplicative model fit some data sets very well. In fact, he found that the rate variable stabilized and improved the predictive ability of his cost model for two out of three airframe production data sets.

The next greatest attention was paid to production break duration. Using an additive model with empirical data on machine shop operations, Pichon and Richardson (1974) found duration of production break to be a statistically insignificant variable for break durations of up to two years. Burns (1976) reports that a General Electric cost accounting bulletin recommends a 50% loss of learning for a 3 to 6 month production break, increasing to a 75% loss for a 12 month break.

Delivery lead time and production lot size also received attention from a fair share of the authors reviewed. Delivery lead time is considered important since it directly determines the time available for preproduction planning, which in turn affects both the first unit cost intercept and the realizable learning function slope (Conway and Schultz, 1959; Keachie, 1964). Production lot size is potentially an important variable since unusually small lot sizes do not permit efficient utilization of manpower and facilities, and unusually large lot sizes overtax production facilities--both extremes being relatively inefficient (Large et al., 1974).

Similarly, production run duration can be an efficiency factor, since it influences the amounts of preproduction planning and of capital investment in machinery and facilities (Conway and Schultz, 1959; Puryear, 1972). However, Large et al. (1974) reported finding no correlation between acceptance span and learning slope in studies of the military airframe industry.

For purposes of the present research, four production related variables were selected for further investigation: production rate (represented alternatively by either the average or the maximum number

of units delivered in a month); production break duration; delivery lead time; and production lot size.

Technical Performance

One remaining train of thought with respect to variables involves the consideration of technical or performance parameters of a product; 13% of the treatises reviewed suggested some form of cost estimating relationship either explicitly recognizing, or at least tempered by, such variables. Brockman and Dickens (1967) experimented with a multiplicative variant of the traditional power form learning model, in which the added variables represented physical characteristics (e.g., speed, weight) of the cargo aircraft under consideration. James (1968) proposed incorporation of a relative (not absolute) complexity factor, to account for shifts in learning induced by product design changes. Booz-Allen (1969) again considered physical product parameters (i.e., electrical parts count, input power) in a model similar to that used by Brockman and Dickens. Batchelder et al. (1969) suggested incorporation of a uniqueness factor, somewhat akin to the complexity factor of James, reasoning that the degree of newness of a design should affect the learning parameters.

Abernathy takes a refreshingly different view of the whole concept of learning, placing it in more of a strategic systems context: "The occurrence of the learning curve is related to the transition of a productive unit, in that it depends on a standardized product design, a reduction in market uncertainty, predictability in organization and work force incentives, and advances in production-process technology" (Abernathy, 1976, pp. 4-14). He emphasizes the need for product

standardization if substantial productivity gains are to be realized; standardization could also be viewed as non-uniqueness.

For purposes of the present research, technical performance parameters will not be explicitly considered. However, the development of either complexity or uniqueness factors (or both) may offer an interesting avenue for future research.

Concepts Addressed

Under the general heading of Concepts, Table 2 reflects the content of each treatise reviewed in terms of six topics: Competitive Effects, Factors of Learning, Learning Curve Hazards, Production Discontinuities, Strategic Implications, and Uses of Learning Theory. Factors of Learning and Uses of Learning Theory have been reviewed in Chapter II. Each of the other four topics will be addressed further in the balance of this section, with emphasis still given to work which leads into the present research.

Competitive Effects

Only 8% of the treatises reviewed have given consideration to competitive effects, and to the potential utility of learning or experience theory in interpreting or anticipating such effects. The first significant work identified in this area is that of Scherer (1964). In analyzing progress curve data on World War II aircraft production programs, he found that "Programs with competition had on the average steeper progress curves than noncompetitive programs" (Scherer, 1964, p. 124). He also recognized that, in spite of the much touted advantages of price competition, the introduction of

second or multiple sources is not always warranted. "When economies of scale are relevant, it could be uneconomical to split up an order just large enough for optimal production by one firm. . . . Only when production orders are expected to be sufficiently large and sustained to permit net cost savings from competition, or when other advantages such as preventing the interruption of deliveries in the event of strikes are important, is second sourcing desirable" (Scherer, 1964, p. 127).

Arditti (1967) points out that, if a firm which develops a new product can sell the initial units of that product less expensively than a potential competitor, then customers will only buy from that competitor if the total procurement cost is lower, due to the competitor's following a steeper learning curve. If the developing firm becomes the initial producer, experience gained will permit it to further reduce its price, making market entry by a competitor more costly. Further, even if production process knowledge were in some way transferred efficiently from the developer and initial producer to the potential competitor, the result would be not only to lower that competitor's initial production costs, but also to flatten his progress curve, thus minimizing the benefits realized from the knowledge transfer. Arditti also notes that, in Government procurements, the threat of developing an alternative source (i.e., separating production from the developer) may serve as an effective prod to the developer, almost like true competition, resulting in reduced total procurement cost.

In studying the cost and price histories of a limited number of military communications-electronics equipment items for which price competition was introduced following the initial few procurements, Booz-Allen (1969) found that the average unit price reduction associated with the introduction of competition was 43%. However, in deference to the limited amount of data supporting that finding, they elected to propose a pricing model incorporating a reduction of only 30% (i.e., reduction to 70% of the precompetitive level). "In conclusion, it is suggested by all of the preceding considerations that a reduction factor of 0.70 can reasonably be expected when a procurement contract goes competitive. This adjustment obviously applies only for the first time the procurement of a device goes competitive, and only after sole source buys provide a cost/quantity relationship" (Booz-Allen, 1969, p. 67). Relying on testimony by former Secretary of Defense McNamara before a Congressional committee in 1965, an Army cost analyst reached a similar conclusion: "In the absence of definable data, it is suggested that a cost reduction of twenty-five percent be considered at the introduction of competition" (Gossett, 1971, p. 13). The term "cost reduction" as used by Gossett referred to a reduction in the price paid by the Army.

Implicit in both of the preceding quotations is the assumption that the reduction in price paid due to the introduction of competition will result only in a vertical shift downwards of the price-quantity curve, and not also in a corresponding change in slope. If, as Scherer found, the slope steepens under competition, then competition is clearly desirable. But if, as Arditti suggested, a flattening of

the slope occurs, the apparent savings due to competition may be illusory, and experience theory views should receive greater attention: "The cost achieved by a large producer can more than offset any benefits from the competition for an equivalent volume spread between several producers. . . . If all production of a given product is concentrated in a single producer, then the cost attainable is about 70 to 80% of what it would be split between two equivalent producers" (Boston Consulting Group, 1972, p. 49).

For purposes of the present research, particular attention will be paid to experience curve slopes as well as vertical shifts following competitive procurements.

Learning Curve Hazards

Learning curve hazards were discussed in fully 41% of the treatises reviewed, and have already been reviewed in Chapter II. However, there are a few points which warrant further emphasis, and they will be brought out here. First and foremost, it must be recognized that there is no underlying, immutable, natural law which dictates that learning will occur in accordance with any particular mathematical formulation. Whether one uses the traditional power form or some more complex model, it is still only an approximation of actual events and relationships, and there is no guarantee that any model will hold true in any specific instance. While learning theory has proven to be a very useful tool for forecasting, it should be used only with great caution as a control device, in recognition of the significant differences existing in patterns of progress (Conway and Schultz, 1959).

Government contractors usually try to demonstrate progress, since "Progress over the length of a contract may carry high 'political' weight for future awards" (Colasuonno, 1967, p. 23); however, there is no guarantee that the progress demonstrated reflects the true progress of which the contractor is potentially capable. It is quite conceivable that "Preoccupation with expected log-linear reductions may mask opportunities for greater reductions" (Colasuonno, 1967, p. 84).

Strict adherence to experience theory, involving intensive capital investment to drive down production costs and a high degree of product standardization to maximize learning opportunities, will necessarily result in reduced capacities for flexibility and innovation (Abernathy and Wayne, 1974). Given the rapidity of technological advances and the attendant high rate of product obsolescence, particularly in the military market place, defense industry contractors should be expecially alert to the dangers posed by the loss of flexibility and innovative capacity. Reductions in these areas should only be permitted to result from conscious decisions to accept such risks, and not from oversight brought about by preoccupation with experience theory.

For purposes of the present research, evidence of preoccupation with expected log-linear price reductions will be sought.

Production Discontinuities

The subject of production discontinuities has been treated in 23% of the treatises reviewed. Wright (1936) and Gibson (1949), as well

as many other authors since them, recognized that production discontinuities resulting from design changes or production breaks should be minimized, if full advantage were to be taken of learning opportunities. For many years, production discontinuities were treated as anomalies, and were either ignored or compensated for by rule-of-thumb adjustments (Colasuonno, 1967). Meyer (1968) proposed recursion formulas for predicting costs when perturbations occur; while of theoretical interest, his approach does not appear to be readily applicable to practical planning problems.

The PhD research reported by Conrad (1969) focused on the effects of intermittent interference with the learning process. Two ways of compensating for learning interruptions were examined by Conrad: 1) Add a constant to the cost value, if the curve following the disruption appeared to be parallel to the curve existing prior to the disruption, or 2) Lag the cycle, if the interruption had the effect of moving subjects backwards to an earlier point in the learning process. While Conrad reached no statistically based general conclusion as to which compensatory treatment should be preferred, he did subjectively judge the lagging approach to typically provide a better fit to empirical data. Ilderton (1970) proposed a mathematical technique for determining an appropriate lag value. Gossett (1971) also favors the lagging technique, although he offers no rationale as to why it should be preferred.

Pichon and Richardson (1974) sought to validate a model which would predict the cost of the first production unit following a production break as a function of the learning curve slope, the cost

of the last unit produced prior to the break, and the duration of the break. Although they had moderate predictive success, they found their production break duration variable to be statistically insignificant (for breaks of up to two years) in their model.

For purposes of the present research, it is clear that a better way needs to be identified for predicting the effects of production discontinuities on product costs and prices. Notwithstanding the results of Pichon and Richardson, the effect of production break duration will be investigated, but in the context of a different model.

Strategic Implications

A surprising 17% of the treatises reviewed contained statements reflecting strategic insights into the experience theory concept. Although key experience effect implications for business strategy have already been presented in Chapter I, and a few relevant quotations from other authors were highlighted at the outset of this chapter, it seems appropriate to consolidate here the strategic views expressed by some of those authors who first drew attention to distinctions between learning and experience theories.

Although Asher did not believe that costs could continue to decline indefinitely as cumulative quantities produced increased, he did foresee the competitive advantage of attaining dominant market share: "Manufacturers who have been producing a given type of product for a long time have a distinct advantage over newcomers in the industry. . . . With luck, and with sufficient financial backing, the newcomer may reach a cumulative output that will put him within reach of his

competitors' production costs" (Asher, 1956, p. 139). Similarly, Keachie (1964, p. 44) realized that "The first producer in a field is already 'down the curve' on his costs when newcomers begin, so they can expect comparable costs only after comparable cumulative production, other things being equal." Two marketing specialists, Kotler (1972) and Jain (1975), both strongly support the philosophy of building market share at the expense of current profits, theorizing that such a strategy should, if successful, maximize long-run profits. Jain also warns producers not to let market share slip away unless there has been a conscious decision to relinquish it.

The fact that technologically based manufacturing process improvements are needed to maintain a semblance of linearity over extended production runs was recognized by Asher (1956). Woolley (1972) also saw the importance of investing in adaptation to technological change.

The strategic nature of experience theory, as a tool for providing insights into the total system which confronts the executive and for allocating men, money, and materials, was seen by Keachie (1964). Combining his own awareness of the need for technological change with Keachie's system perspective, Woolley (1972, pp. 46, 47) stated: "The concept of the experience curve is essentially that of the total firm as a system, innovating, adapting to technological change, and reacting to the pressure to reduce costs."

Arditti (1967) emphasized the importance of considering both initial costs and learning slopes together when attempting to develop a procurement strategy involving multiple sources. He recognized the fallacy in considering slopes alone, without regard to price level.

Finally, Abernathy and Wayne (1974) and Abernathy (1976) writing alone raise caution flags about the advisability of indiscriminately pursuing a cost minimization strategy, which they equate to experience theory. "Many years of high rates of productivity have come at a cost--a declining capacity for innovation. . . . To achieve gains in productivity, there must be attendant losses in innovative capability; or, conversely, the conditions needed for rapid innovative change are much different from those that support high levels of production efficiency" (Abernathy, 1976, pp. 1-2, 1-3). Although Abernathy was writing about the automotive industry, his conclusions appear to be at least equally applicable to the aerospace industry. In fact, in the aerospace industry in particular, flexibility and innovative capability may be of far greater long-run value than the ability to produce obsolescent products at a minimal cost.

For purposes of the present research, emphasis will be placed on verifying the applicability of price experience curve theory in the military market place. If applicability in spite of Government controls and interventions can be established, then strategy implications counterpart to those for business strategy in consumer and industrial markets can be inferred.

CHAPTER IV — RESEARCH METHODOLOGY

In this chapter, the research methodology is explained. The research is organized around the seven issues identified in the introductory chapter. In addition to further discussion of each of the research issues, this chapter presents hypotheses to be tested, analytical models and procedures to be used, and statistical tests to be employed in the course of the analyses.

Research Issues

Based on a review of the literature relevant to experience curve theory, and on the author's personal knowledge of Department of Defense avionics acquisition practices, a set of seven related issues which warrant further research has been identified. Clearly, many other issues could be raised, and numerous other questions could be addressed. However, these seven issues have been selected as being particularly worthy of further investigation. Although already listed in Chapter I, they are repeated here for convenient reference. (More precise statements, in hypothesis form, are presented later in the chapter.)

1. How do experience curves differ from traditional learning curves in the Government procurement environment?
2. How are the forms of experience curves affected by alternative techniques for compensating for the effects of inflation?

3. How are the forms of experience curves affected by implicit prior experience on closely related products?

4. How are the forms of experience curves related to production lot sizes, product delivery rates, delivery lead times, and the durations of breaks between production runs?

5. How stable are experience curve slopes over successive procurements?

6. How consistent are experience curve slopes within and across firms?

7. How accurately can future procurement pricing be predicted using experience curve theory?

In subsequent sections of this chapter, each of these issues will be discussed, and the planned analytical approach to the investigation of each will be described. At the end of this chapter, the various alternative multiplicative power form models of learning and experience employed in the course of investigating these issues will be summarized. Each of these models shares the advantage of being readily transformable into an additive logarithmic model, amenable to bivariate and multivariate regression analyses.

The non-random selection of the data base content limits the utility of statistical tests, and the transformation to logarithmic formulation distorts the usual interpretation of such established indicators as the Coefficient of Determination (R^2) and F-tests (which are not particularly robust under conditions of skewness). In spite of these limitations, selective use is made of F-tests of explanatory

significance, R^2 and Adjusted R^2 values, and Standard Error of Estimate (SEE) values in comparing alternative models. Examination of regression residuals plays an important role in determining the applicability of models, particularly with respect to Issue 5, in which the question of piecewise log-linearity is examined. Other statistical tests of relationships, such as t-tests and chi-square tests, are also used extensively.

Required analyses were performed using FORTRAN programs written by the author, augmented by prepackaged SPSS (Statistical Package for the Social Sciences) routines (Nie et al., 1975). Graphic plots and summary tables of results are presented as necessary to clarify the narrative description of results.

Experience Vs. Learning

Issue 1: How do experience curves differ from traditional learning curves in the Government procurement environment? Experience curves may be viewed as an approximation to the summation of a whole set of learning curves, individually applicable to the elements which collectively comprise a particular product. That is, distinct learning curves may be considered to exist for direct fabrication labor, direct assembly labor, purchased materials, etc., and for the related overhead accounts. At varying levels of aggregation of these subsidiary learning curves, the experience effect may be reflected in the direct costs of value added (the traditional learning theory view), in total manufacturing costs, in total costs, or in market price (most convenient for strategic analysis). An inherent part of the experience

effect may well involve learning by customers, as reflected in increasingly effective interactions and cooperation between customers and producers. For example, customer feedback influences such cost factors as product design and channels of distribution, as well as price.

The Boston Consulting Group has found that the experience effect is apparent in numerous consumer and industrial products manufactured and sold in strongly competitive market environments. They have found (and Woolley has confirmed) strong empirical evidence to suggest that, in such markets, price follows cost, and thus experience is adequately reflected in depictions of cumulative average market price versus cumulative quantity sold. However, The Boston Consulting Group (1972, p. 44) cautions that "Experience curves do not apply if major elements of cost or price are determined by patent monopolies, natural material supply, or Government regulation."

Department of Defense procurements impose very extensive Government regulations on contractors, and the few-sellers, very-few-buyers (oligopolistic, oligopsonistic) defense market place differs markedly from the strongly competitive consumer and industrial markets examined by The Boston Consulting Group and by Woolley. For instance, defense procurements are usually made only in annual increments, authorized and funded at the discretion of Congress. The uncertainty thus surrounding future orders is a severe disincentive to capital investment, resulting in less than optimal efficiency and productivity. Productivity enhancement is further handicapped by the particularly rapid onset of obsolescence, unfortunately characteristic of the

high technology products required by the defense community (Ulsamer, 1976).

Long lead-times between major project startup and completion are the rule, not the exception. Non-standard designs are common, and the contractor's technical risks are multiplied by Government intervention in both product and process design changes. Although regulations imposed by the Government impact most contractors in such areas as safety, labor standards, and financial reporting, defense contractors are also subjected to stringent Government controls on quality, security, subcontracting, and documentation. Defense urgency often dictates unusually demanding delivery schedules, cutting delivery lead times and severely constraining preproduction planning activities (Spencer, 1977).

In view of these unique features of the military market place, it is appropriate to compare cost-based learning curves at various levels of aggregation with price-based experience curves, to determine the degree to which the experience effect pertains under such constrained market conditions.

Both the classical power form model attributed to Wright

$$Y_A = B_0 X_1^{B_1} \tag{16}$$

and the modified power form model attributed to Crawford

$$Y_U = B_0 X_1^{B_1} \tag{17}$$

were employed in this analysis. The variables contained in each case analyzed, and the relationships amongst equipment items, contractors, and subfiles, will be delineated in the next chapter. To the extent

permitted by available data (see Table 6), each model was examined with the dependent variable representing four different classifications or levels of learning or experience:

A) Direct Labor Cost per Unit,

B) Purchased Material Cost per Unit,

C) Total Manufacturing Cost per Unit, and

D) Price per Unit.

In the classical model, Y_A represents cumulative average unit cost or price, whereas in the modified model, Y_U represents unit cost or price directly. In both models, X_1 represents the cumulative quantity of units produced, B_0 is a scale factor implicitly related to the cost or price of the initial unit produced, and B_1 is the factor which determines the steepness of the learning or experience curve slope. All analyses of this issue incorporated cost and price deflators based on Federal Purchases of Goods and Services indices.

For each item-contractor combination analyzed, the overall regression slopes, with associated coefficients of determination and significance levels, were determined for each level of prices and costs for each model. These results are summarized and compared in Chapter VI.

Paired-sample, two-tailed t-tests were performed to compare the sample means of product price experience curve slopes with those of each of three cost accounting classifications; these tests were performed for four populations and for both Cumulative Average theory and Unit theory. The cost accounting classifications were direct labor, purchased material, and total manufacturing costs. The

TABLE 6 — CASES FOR WHICH COST AND SCHEDULE DATA ARE AVAILABLE

Item	Contractor 6	Contractor 10	Contractor 11
1	-	32	-
2	-	13	-
3	-	28	-
4	23	-	-
5	-	-	7
6	-	-	3
8	19	-	-
9	9	-	-
10	-	-	18
11	-	-	3
12	-	-	5
13	-	18	-
14	-	29	-
15	-	30	-

NOTE: Cell entries represent the number of procurement cases available for analysis for each item-contractor combination shown.

populations were the work of each of the three contractors (i.e., 6, 10, and 11) individually and their total work (composite). Stated formally,

$$H_0: \mu_P = \mu_C \quad \text{vs.} \quad H_A: \mu_P \neq \mu_C$$

where μ_P and μ_C represent the mean price and cost slopes, respectively. The significance criterion for rejection of the null hypothesis was in all instances 5%.

Paired-sample, one-tailed t-tests were performed to compare the sample means observed under the cumulative average theory with those observed under the unit theory, for four populations and four accounting classifications. The populations were the work of each of the three contractors (i.e., 6, 10, and 11) individually and their total work (composite). The accounting classifications were direct labor, purchased material, and total manufacturing costs, and product prices. Stated formally,

$$H_0: \mu_C = \mu_U \quad \text{vs.} \quad H_A: \mu_C > \mu_U$$

where μ_C and μ_U represent the mean slopes under cumulative average theory and unit theory, respectively. The significance criterion for rejection of the null hypothesis was in all instances 5%.

In addition to these statistical tests and comparisons, the predictability of price experience slope as an additive function of direct labor, purchased material, and total manufacturing cost slopes is also reported.

Alternative Inflation Treatments

Issue 2: How are the forms of experience curves affected by alternative techniques for compensating for the effects of inflation? The Boston Consulting Group elected to use implicit price deflators based on the Gross National Product (GNP) in their investigations. Other choices could be made, ranging from ignoring inflation entirely to applying implicit deflators more closely tailored to a particular industry or procurement environment. Ignoring inflation entirely would simplify analyses, but could distort the slopes of experience curves, possibly leading to erroneous inferences. Applying closely tailored deflators would seem to be more appealing, but might not affect the slopes of experience curves (and thus the inferences made from them) enough to warrant the added analytical complexities introduced. It is thus of importance to examine the relative effects of alternative treatments of inflation, seeking to identify an approach which provides an appropriate balance between analytical simplicity and inferential power. The implications of this aspect of the present research should be broadly applicable, not limited to defense avionics.

Only the classical power form model attributed to Wright

$$Y_A = B_0 \, X_1^{B_1} \tag{16}$$

was employed in this analysis, using price as the dependent variable. Four alternative treatments of inflation were evaluated for each item-contractor and item-industry combination examined:

A) Federal Purchases of Goods and Services (FPGS) Deflators,

B) Gross National Product (GNP) Deflators,

C) Avionics Procurement (AVPR) Deflators, and

D) Ignore Inflation.

The overall regression slopes resulting from each of these treatments are summarized and compared in Chapter VI. Paired-sample, one-tailed t-tests were performed to compare the sample regression slope means observed under the four alternative inflation treatments for the 28 item-contractor combinations analyzed. Stated formally, the six tests were

$$H_{01}: \mu_A = \mu_B \quad \text{vs.} \quad H_{A1}: \mu_A < \mu_B$$

$$H_{02}: \mu_A = \mu_C \quad \text{vs.} \quad H_{A2}: \mu_A > \mu_C$$

$$H_{03}: \mu_A = \mu_D \quad \text{vs.} \quad H_{A3}: \mu_A < \mu_D$$

$$H_{04}: \mu_B = \mu_C \quad \text{vs.} \quad H_{A4}: \mu_B > \mu_C$$

$$H_{05}: \mu_B = \mu_D \quad \text{vs.} \quad H_{A5}: \mu_B < \mu_D$$

$$H_{06}: \mu_C = \mu_D \quad \text{vs.} \quad H_{A6}: \mu_C > \mu_D$$

where μ_A, μ_B, μ_C, and μ_D represent respectively the mean slopes of the four treatments identified above. If the alternative hypotheses could all be accepted, the implied ordering of inflation treatments in terms of slope steepness would be D (flattest), B, A, and C (steepest). This implied ordering is consistent with the hypothesis that the most closely tailored deflator will lead to the steepest slopes, with progressively more gradual slopes resulting from the use of progressively less closely tailored deflators. In addition to these tests of relative slope steepness, goodness of fit criteria, in the form of the mean coefficients of determination, significance levels, and standard error of

estimate values associated with the alternative treatments, will also be examined. Finally, the alternative treatments will be ranked in terms of their relative performance under each of these criteria.

The item-contractor and item-industry combinations analyzed are those identified in Table 7 (i.e., all cases for which adequate price data are available). The cell entries in Table 7 again represent the number of procurement actions available for analysis for each item-contractor and item-industry combination.

Implicit Prior Experience

Issue 3: How are the forms of experience curves affected by implicit prior experience on closely related products? New products are frequently variants of older products, often incorporating components, subassemblies, and manufacturing processes with which the manufacturer has already attained extensive experience. Similarly, an extended break in production, resulting in some loss of learning, can create a situation in which new production should not be treated in the conventional manner (i.e., starting all over from unit one). Rather, credit should be given in some way for implicit prior experience, recognizing that the current production is not totally new, and that not all prior experience has been lost. The concept behind the "Stanford-B" curve touched on this notion, but has not been pursued at length, possibly because of the emphasis on an assumed constant learning slope of 70.7%.

A variant of the classical power form model and of the Stanford-B equation

TABLE 7 – CASES FOR WHICH PRICE DATA ARE AVAILABLE

Item	Contractor 1	2	3	4	5	6	7	8	9	10	11	12	13	ALL
1	-	-	-	-	-	-	-	-	-	35	-	-	-	-
2	-	-	-	-	-	-	-	-	-	16	-	-	-	-
3	-	-	-	-	-	-	-	-	-	31	-	-	-	-
4	-	-	-	-	-	23	-	-	-	-	-	-	-	-
5	-	-	-	-	-	-	-	-	-	-	7	-	-	-
6	-	-	-	-	-	-	-	-	-	-	3	-	-	-
7	7	-	4	-	-	7	-	-	1*	-	-	-	-	19
8	-	-	-	-	-	19	-	-	-	-	-	-	-	-
9	-	-	-	-	-	9	-	-	-	-	-	-	-	-
10	-	-	-	-	-	-	-	-	-	-	18	-	-	-
11	-	-	-	-	-	-	-	-	-	-	3	-	-	-
12	-	-	-	-	-	-	-	-	-	-	5	-	-	-
13	-	-	-	-	-	-	-	-	-	21	-	-	-	-
14	-	-	-	-	-	-	-	-	-	31	-	-	-	-
15	-	-	-	-	-	-	-	-	-	33	-	[illegible]	-	-
16	-	18	-	-	-	-	-	-	-	-	-	-	-	-
17	-	-	-	-	-	-	-	18	-	-	-	2	-	20
18	-	-	-	-	-	-	-	17	-	-	-	-	-	-
19	-	-	-	1*	3	7	1*	-	-	-	-	-	5	17
20	-	-	-	1*	4	7	2	-	-	-	-	-	6	20

* Insufficient data available to analyze item-contractor combination, but contractor included in item-industry ("ALL" contractor) analyses.

$$Y_A = B_0 \, (X_1 + C)^{B_1} \tag{18}$$

was employed in this analysis, using price as the dependent variable and FPGS deflators. The parameters B_0 and B_1 were both determined by linear regressions on the logarithmically transformed equation

$$\ln Y_A = \ln B_0 + B_1 \ln (X_1 + C) \tag{19}$$

The factor C, representing a coordinate shift (and frequently associated with an implicit prior experience production quantity), was assigned values 10^j and 3×10^j for $j = 0, 1, \ldots, 5$. The logarithmic spacing of the C values examined was chosen to accommodate the wide range of C values over which the slope of equation (19) shifts from nearly horizontal to nearly vertical.

In essence, the effect of the Stanford type transformation is to introduce a shift factor to the coordinate system, as illustrated in Figure 4. When the give data break sharply from a gradual slope to a steeper slope, represented by segments (1) and (2) in the figure, a regression equation fitted to the overall data set, as represented by segment (3), does not provide a very good statistical fit. (The merits of piece-wise log-linearity, as represented by segments (1) and (2), will be addressed in conjunction with Issue 5.) Introduction of a shift factor deemphasizes the slope break, resulting in a more nearly linear representation of the transformed data set, as is apparent in segment (4).

To determine the validity of interpreting the shift factor (C) values as implicit prior experience quantities, it would be necessary to compare these values with explicitly known prior experience quantities.

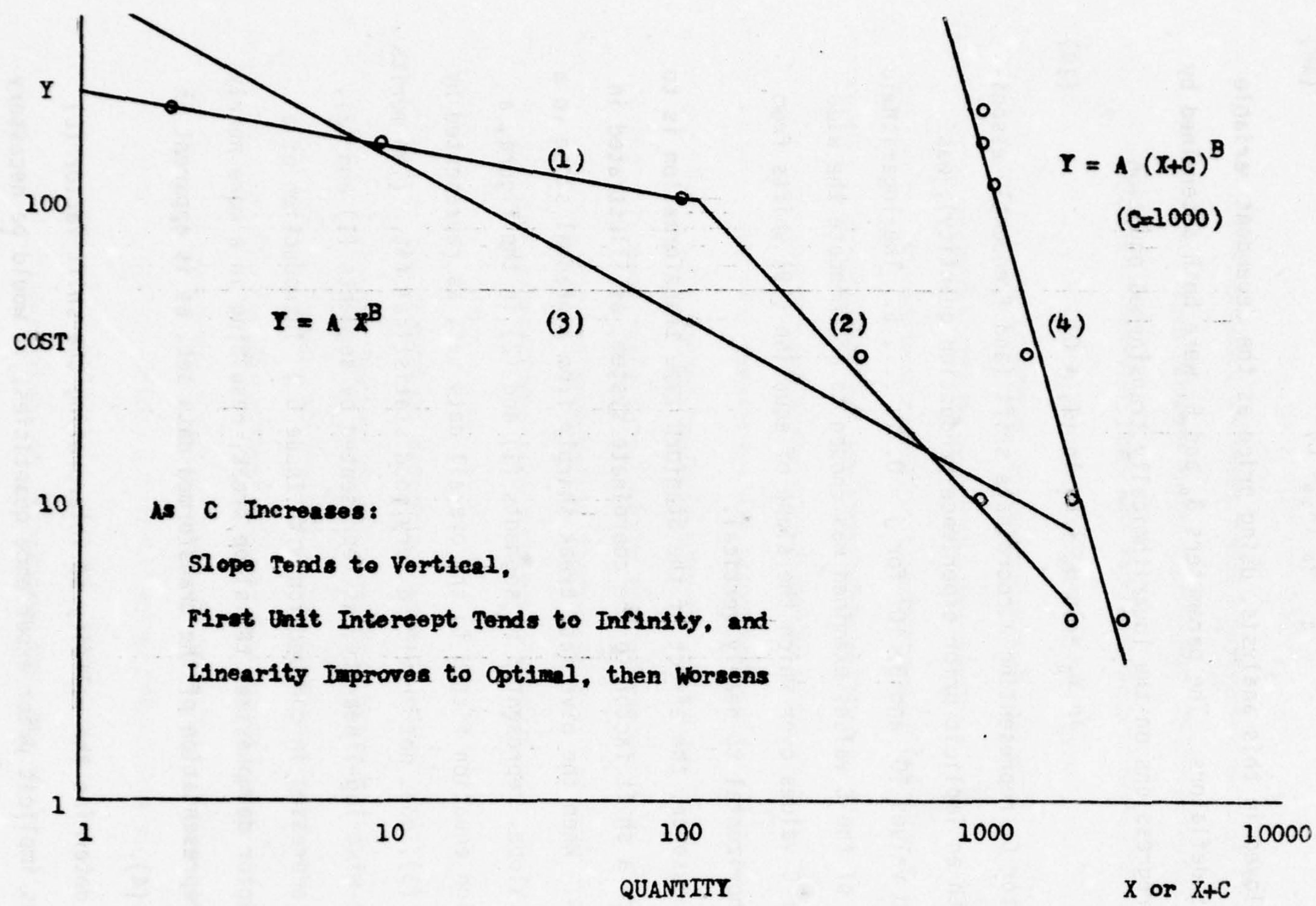


FIGURE 4 — COMPARISON OF TRADITIONAL AND STANFORD LEARNING EQUATIONS

Since such explicit data were not available for this research, all that can really be determined is whether or not the shift factors established in the present research are consistent with those previously found in the Stanford research. If substantial inconsistencies are found, alternative hypotheses should be formulated and tested in further research.

Prior to conducting the regression analyses just described, it was anticipated that about 50% of the subfiles examined would show improved statistical fits under this transformation (i.e., an equal chance that any particular subfile would or would not show improvement), and that the optimal shift factor value would typically not exceed 300, consistent with the Stanford Research Institute findings reported earlier. The item-contractor and item-industry combinations analyzed were again those identified in Table 7, except excluding item-contractor combinations with fewer than 3 cases. The observed responses of several parameters to changing shift factor (C) values will be reported in Chapter VI. These parameters include R^2 (the coefficient of determination, estimating the percent of variance explained), Adjusted R^2 (a more conservative estimate of the percent of variance explained, considering the number of independent variables and the number of cases), Standard Error of Estimate (the standard deviation of the residuals), F-ratios (implying the statistical significance of the regression relationship), the imputed first unit intercept value, and the slope exponent value.

Production Parameters

Issue 4: How are the forms of experience curves related to production lot sizes, product delivery rates, delivery lead times, and the durations of breaks between production runs? The traditional power form model of learning does not explicitly consider such additional components of the experience effect as investment, specialization, and scale. In an effort to recognize these components more directly, a new model will be examined, introducing the production parameters considered here as implicit indicators of those experience components. These parameters are presumably related to the cited experience factors through a variety of managerial decisions. Selection of these specific parameters was based both on traditional economic theory with regard to their effects and on the availability of consistently measurable data. While the inferences to be made in the present research are necessarily limited to avionics procurements, the methodology proposed here should be equally applicable in other contexts.

Five specific production parameters were selected for investigation: Quantity Bought (number of units in lot), Maximum Delivery Rate (units per month), Production Break Duration (number of months), Delivery Lead Time (number of months), and Average Delivery Rate (units per month). The expected effect of each of these parameters (and of Cumulative Quantity) on price, as predicted by traditional economic theory, is depicted in Figure 5. Although these curves are not themselves of the power form, it is proposed that the region of concern of each, for purposes of the present research, can be approximated

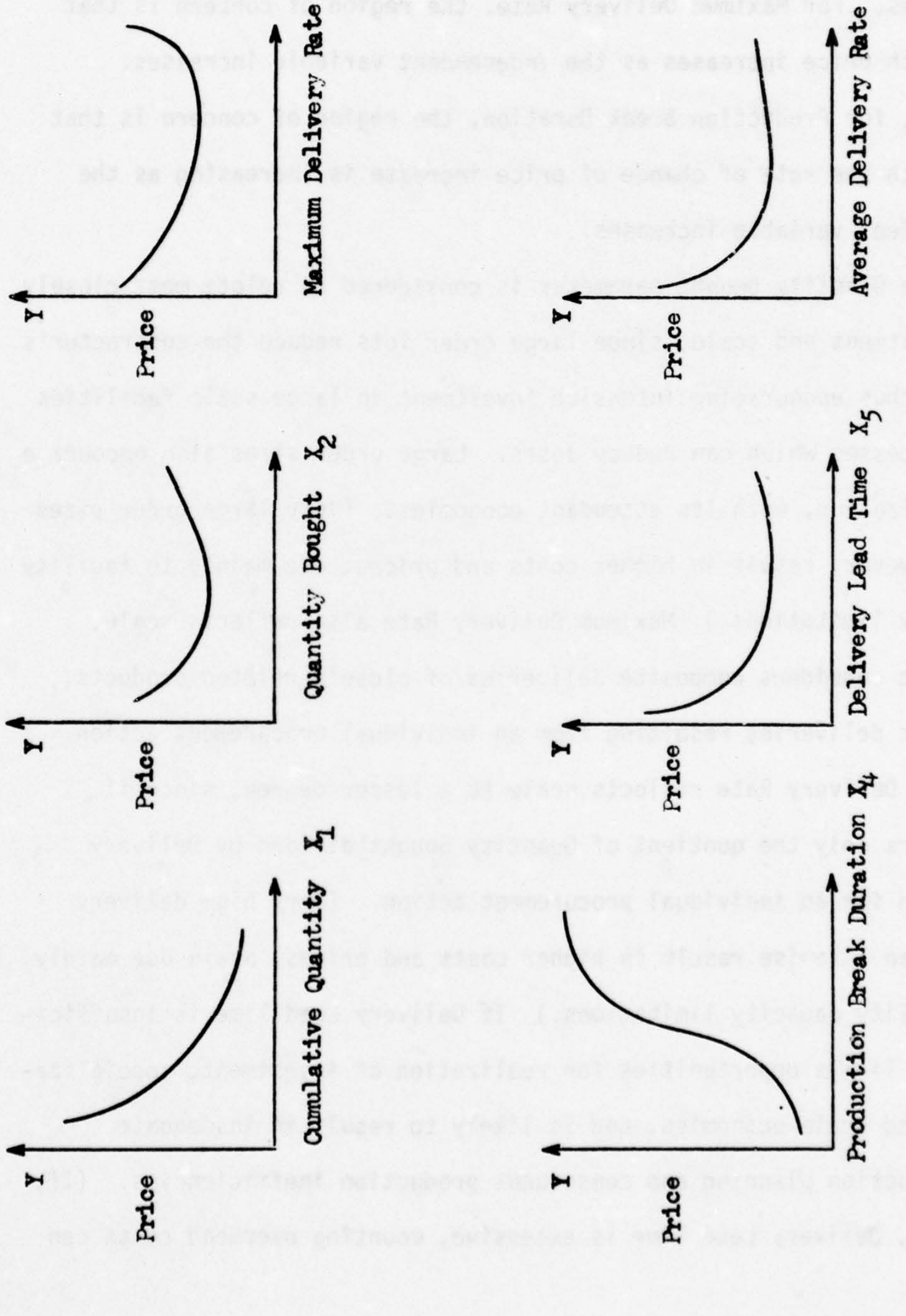


FIGURE 5 EXPECTED PRODUCTION PARAMETER EFFECTS ON PRICE

adequately by a simple power form relationship. Thus for Quantity Bought, Delivery Lead Time, and Average Delivery Rate, the region of concern is that for which price decreases as the independent variable increases. For Maximum Delivery Rate, the region of concern is that for which price increases as the independent variable increases. Finally, for Production Break Duration, the region of concern is that for which the rate of change of price increase is increasing as the independent variable increases.

The Quantity Bought parameter is considered to relate most closely to investment and scale, since large order lots reduce the contractor's risks, thus encouraging intensive investment in large scale facilities and processes which can reduce costs. Large order sizes also encourage specialization, with its attendant economies. (Very large order sizes can, however, result in higher costs and prices, due mainly to facility capacity limitations.) Maximum Delivery Rate also reflects scale, since it considers composite deliveries of closely related products, not just deliveries resulting from an individual procurement action. Average Delivery Rate reflects scale to a lesser degree, since it considers only the quotient of Quantity Bought divided by Delivery Duration for an individual procurement action. (Very high delivery rates can likewise result in higher costs and prices, again due mainly to facility capacity limitations.) If Delivery Lead Time is insufficient, it limits opportunities for realization of investment, specialization, and scale economies, and is likely to result in inadequate preproduction planning and consequent production inefficiencies. (If, however, Delivery Lead Time is excessive, mounting overhead costs can

force prices up.) Finally, if Production Break Duration exceeds a few months, specialized facilities and personnel are likely to be diverted to other efforts, resulting in a major loss of experience.

To investigate the effects of these production parameters in conjunction with the learning effect on avionics prices, a multiplicative variant of the classical power form model, similar in form to Levenson's model (equation 12), was employed:

$$Y_A = B_0\, X_1^{B_1}\, X_2^{B_2}\, X_3^{B_3}\, X_4^{B_4}\, X_5^{B_5}\, X_6^{B_6} \tag{20}$$

Actually, an additive logarithmic transformation of this model was evaluated, using stepwise multivariate regression techniques:

$$\ln Y_A = \ln B_0 + B_1 \ln X_1 + B_2 \ln X_2 + B_3 \ln X_3 + B_4 \ln X_4 + B_5 \ln X_5 + B_6 \ln X_6 \tag{21}$$

In these models, Y_A represents cumulative average unit price, B_0 represents the imputed first unit price, and B_1 through B_6 are the regression determined parameters defining the effect of each of the independent variables, as summarized in Table 8. In essence, the main determinant of price is the learning effect, reflected in Cumulative Quantity variable X_1 and its associated slope exponent, B_1. Each of the other factors serves to modulate the price, shifting it above or below the level determined by learning alone.

In employing the regression model of equation (21), it was planned in advance that the modulation effects of variables would not be considered significant unless the null hypotheses of the slope exponents being equal to zero could be rejected at a 5% criterion. Stated formally,

TABLE 8 — VARIABLES AND EXPECTED PARAMETER SIGNS

Variable	Description	Parameter	Sign
X_1*	Cumulative Quantity	B_1	-
X_2	Quantity Bought	B_2	-
X_3	Maximum Delivery Rate	B_3	+
X_4**	Production Break Duration	B_4	+
X_5	Delivery Lead Time	B_5	-
X_6***	Average Delivery Rate	B_6	-

$$Y_A = B_0 \prod_{i=1}^{6} X_i^{B_i}$$

* $X_{1J} = \sum_{J=1}^{J} X_{2j}$ (where j represents lot number)

** X_4 = (Production Break Duration in Months) + 1 in order to avoid taking the logarithm of zero

*** X_6 = (Quantity Bought)/(Delivery Duration)

$$H_0: B_i = 0 \quad \text{vs.} \quad H_a: B_i \neq 0 \quad (i = 2, 3, \ldots, 6)$$

However, it became apparent in the course of the analyses that even variables whose coefficients did not meet this test of statistical significance could contribute substantively to both explanation of variance and reduction in standard error of estimate values. Since regression coefficient magnitudes near zero are meaningful in the production parameter model, these latter criteria were used in determining which variables to consider, rather than the usual statistical test. The absolute magnitudes of B_2 through B_6 were expected to be less than 0.10000, in keeping with the concept of modulation effects as distinct from main effects, with signs expected to be as indicated in Table 8.

The objective of this part of the present research was to determine which (if any) of the proposed production parameters, introduced in the model of equation (21), offer a significant explanatory advantage relative to the classical power form model. For each production sequence analyzed, the results observed will be presented in terms of the effects of the production parameters on explained variance and on the Standard Error of Estimate. Ideally, the former should increase and the latter should decrease as significant variables are added to the model. Additionally, the imputed learning slopes before and after the introduction of production parameters will be compared, using a paired-sample two-tailed t-test. Stated formally,

$$H_0: \mu_B = \mu_A \quad \text{vs.} \quad H_A: \mu_B \neq \mu_A$$

where μ_B and μ_A represent the mean slopes before and after, respectively.

The item-contractor combinations analyzed are identified in Table 6.

Piecewise Log-Linearity

Issue 5: How stable are experience curve slopes over successive procurements? It seems reasonable to expect changes in experience curve slope from one period in a product's life cycle to another, due for instance to advancing process and product maturity, and perhaps also to changes in production scale. Are there such changes, and do they reveal identifiable patterns? Prior analyses of learning phenomena by various investigators (notably Asher, 1956) suggest that a "reversed-S" shaped curve (perhaps approximated by log-linear segments) in a logarithmic plane may be more appropriate than the standard assumption of a strictly log-linear learning or experience relationship. Especially for short-term projections, bivariate regression on log-linear segments (if applicable) should offer a simpler, more accurate tool than multivariate regression. Great care must be exercised, however, to minimize the risks of relying on such a simplified tool when in fact a changing environment demands the use of more complex techniques.

Only the classical power form model attributed to Wright

$$Y_A = B_0 \, X_1^{B_1} \tag{16}$$

was employed in this analysis, using price as the dependent variable and FPGS deflators. The appearance and structure of each plot of the natural logarithm of cumulative average unit price versus the natural logarithm of cumulative quantity produced were examined (see Appendix C for those plots), and plots were tentatively divided into piecewise

log-linear segments when discontinuities were apparent. The validity of each of the selected break points was checked by examining regression residuals to confirm deviations from linearity.

It was hypothesized that another indication of slope stability could be obtained by examining the standard deviation of adjacent slopes. The adjacent slope by definition is the slope from the most recent prior procurement to the current procurement in a sequence, mathematically determined without recourse to regression techniques. It was thought that a "high" standard deviation of adjacent slopes for a procurement sequence would be suggestive of one or more well-defined breaks in that sequence's overall slope. For purposes of the present research, standard deviation values greater than those characteristic of the lowest third of the subfiles were defined as "high." A chi-square frequency comparison test was performed to determine if the selection of subfiles demonstrating piecewise log-linearity characteristics was significantly associated with high standard deviation values for adjacent slopes. Stated formally,

$$H_0: \ f_H = 2f_L \quad \text{vs.} \quad H_A: \ f_H \neq 2f_L$$

where f_H and f_L represent respectively the frequencies of high and low standard deviations of adjacent slopes for subfiles selected for piecewise log-linearity analyses. A rejection criterion of 5% was predetermined.

A paired-sample, two-tailed t-test was performed to compare mean adjacent price experience slopes with counterpart regression price

experience slopes, both determined under cumulative average theory with FPGS deflators. Stated formally,

$$H_0: \mu_R = \mu_A \quad \text{vs.} \quad H_A: \mu_R \neq \mu_A$$

where μ_R and μ_A represent regression and adjacent slope means, respectively. Acceptance of the null hypothesis of equality of the underlying population means would substantiate the applicability of adjacent slope values in these analyses.

The item-contractor and item-industry combinations initially examined were those identified in Table 7, except that combinations with fewer than four procurement actions could not be evaluated due to insufficient degrees of freedom. The 15 subfiles actually selected for regression analyses are identified in Table 9; cell entries in that table indicate the number of procurements analyzed.

For each piecewise log-linear segment examined, key regression characteristics (i.e., coefficient of determination, standard error of estimate, significance, and slope) will be reported and compared with the counterpart overall regression characteristics for that subfile. The expected findings for each subfile were that coefficient of determination values would increase and standard error of estimate values would decrease for each segment, as contrasted with the corresponding overall regression characteristics for that subfile. Comparisons of regression relationship significances and of experience slopes were expected to be inconclusive. Significance improvements associated with better fits were expected to be offset by significance degradations due to fewer data points. Slope steepness is dependent on the nature of

TABLE 9 — SUBFILES ANALYZED FOR LOG-LINEARITY

Subfile	Segments First	Segments Middle	Segments Last
01	13	-	23
03	3	3	27
04	12	-	12
09	4	-	4
10	7	-	13
12*	6	-	3
13	3	6	11
18	3	13	19
19	4	10	6
20	3	-	16
22	4	-	17
23	7	4	8
27*	7	5	6
31	3	-	4
32*	8	6	7

* Initial procurement data point omitted as an apparent outlier, not fitting a segment pattern.

NOTE: Cell entries indicate the number of procurements analyzed.

the underlying data, and no consistent shift pattern was anticipated. Comparisons of all four characteristics between last segment and first segment values were expected to be inconclusive.

Chi-square frequency comparison tests were performed to test the significance of membership differences in the categories Relative Increase and Relative Decrease. A total of 12 tests were performed, three for each of the four regression characteristics compared: first segment vs. overall, last segment vs. overall, and last segment vs. first segment. (Since only seven subfiles were judged to have middle segments, no statistical tests were appropriate for those segments.) All tests were of the form

$$H_0: f_I = f_D \quad \text{vs.} \quad H_A: f_I \neq f_D$$

where f_I and f_D represented the frequencies of Relative Increase and of Relative Decrease, respectively. A rejection criterion of 5% was again predetermined. Strictly interpreted, chi-square tests of this sort are only applicable when the observations are independent. In these analyses, the tests were made in spite of the fact that common underlying factors (e.g., same contractor or same product design) might be expected to exert similar influences on the behavior of several subfiles, thus negating the assumption of strict independence.

Slope Variability

Issue 6: How consistent are experience curve slopes within and across firms? It is common practice when forecasting the experience pattern of a new product to use the slope value for a similar product within the firm or industry, or in some cases even to use firm or

industry average values. As reported in Chapter III, Harris et al. (1965) have recommended an order of desirability for alternative methods of approximating an unknown slope. Since slopes seem to be determined mainly by the interaction of product and process design factors with production parameters, product life cycle stage, and managerial strategies, the question arises as to whether or not it is reasonable to apply an experience slope observed on one product or class of products within a firm to projections of the probable behavior of other products. Further, it is expected that enough differences do, in fact, exist from one firm to another to raise serious doubts about the validity of using industry average experience slopes as representative of individual firms' capabilities.

No additional regressions were required for this analysis, as regression characteristics generated in conjunction with the analysis of Issue 2 were adequate. Since a high degree of consistency between slope values is associated with low variability amongst observations, comparisons were made on the basis of the standard deviations of regression slope values, considered in conjunction with mean and extreme slope values. Comparisons were made across products (items) within firms 5, 6, 8, 10, 11, and 13, and for the cross-contractor composite ALL (reference Table 7), which encompassed work done by ten contractors. Comparisons were made across firms for products (items) 7, 17, 19, and 20. Finally, comparisons were made amongst communications equipment subfiles, navigation equipment subfiles, and a composite of all subfiles available for analysis.

To facilitate comparisons, it would help to know a "desirable" slope standard deviation value. If slopes are assumed to be normally distributed, then a "desirable" maximum value for slope standard deviation is .01276; this standard deviation value corresponds to 95% confidence that slope values will be within 5% of one another (i.e., ±2.5% of the mean at a nominal slope of 100%).

In view of the very limited data available to support this aspect of the present research (i.e., not more than six items made by any one firm, and not more than four firms making any one item), no statistical tests could reasonably be applied. Results reported should therefore be taken as suggestive of possible relationships subject to further confirmation, rather than as well-founded inferences with widespread implications.

Future Price Prediction

Issue 7: How accurately can future procurement pricing be predicted using experience curve theory? It is generally recognized that the theory of experience curves seeks to emphasize the inferences which can be made at a strategic or "macro" level, rather than to support specific detailed estimates or projections of costs or prices, particularly in the near term. (Learning theory, on the other hand, is sometimes used for manufacturing control purposes.) However, if it were possible to extract relatively "micro" projections from knowledge of recent market prices and various factors influencing production, the simplicity associated with working from price-based data augmented by relatively insensitive contractor characteristics

(e.g., demonstrated responses to alternative production break durations, and to varying delivery rate requirements) would make such a price projection technique valuable. In view of this, experience theory based price predictions were made and tested.

In Government weapons system and subsystem procurements, it is usually not necessary to project future buy prices more than two or three buys beyond the current one. Consequently, holdout samples consisting of the three most recent procurements for each item-contractor and item-industry combination having adequate data were compared with predictions of those sample values based on regression models developed from the reduced number of procurement cases. The procurement sequence subfiles containing sufficient individual procurement actions to permit comparative evaluations of two or more forecasting methods are identified in Table 10. The four forecasting methods investigated combined two data base subsets with two models:

A) Overall Regression, Traditional Model,

B) Overall Regression, Production Parameter Model,

C) Last Log-Linear Segment Regression, Traditional Model, and

D) Last Log-Linear Segment Regression, Production Parameter Model.

Each method was used to predict cumulative average unit price for one, two, and three buys beyond the range of the data used in constructing the regression models.

The results obtained from the four different forecasting methods are summarized, and the methods are ranked in terms of their apparent relative predictive abilities. Whereas earlier evaluations were made

TABLE 10 — PRICE PREDICTION CASES ANALYZED

Subfile	Prediction Method* Comparisons AB	AC	ABCD
01	X	X	X
02	X		
03	X	X	X
04	X	X	X
10		X	
11	X		
13	X	X	X
16	X		
17	X		
18	X	X	X
20		X	
22		X	
Totals	9	8	5

* A: Overall Regression, Traditional Model

B: Overall Regression, Production Parameter Model

C: Last Log-Linear Segment Regression, Traditional Model

D: Last Log-Linear Segment Regression, Production Parameter Model

NOTE: Method comparison opportunities were restricted by data limitations to the combinations shown (i.e., AB, AC, ABCD).

on parameters such as the Standard Error of Estimate, this analysis is based on actual and forecast cumulative average dollar prices (FPGS deflator adjusted). The measures of predictive ability considered include MAD (Mean Absolute Deviation), Bias (average deviation), and Theil's U (which introduces the notion of variance as well as deviation). These measures are defined as follows:

$$\text{MAD:} \quad Q_n = \frac{\sum_{i=1}^{n} |F_i - A_i|}{n} \tag{22}$$

$$\text{Bias:} \quad V_n = \frac{\sum_{i=1}^{n} (F_i - A_i)}{n} \tag{23}$$

$$\text{Theil's U:} \quad U_n^2 = \frac{\sum_{i=1}^{n} (F_i - A_i)^2}{\sum_{i=1}^{n} F_i^2} \tag{24}$$

For each of these measures, F_i and A_i represent forecast and actual values, respectively, for subfile i. Also for each, small magnitudes (of Q, V, or U) indicate better predictive ability than large ones. In recognition of the substantial differences from one subfile to another in actual price levels, the measures are computed on a normalized (percentage) basis as well as on observed dollar values. A key advantage of the normalized comparisons is the applicability of statistical tests, not meaningful with the raw observed dollar deviation values.

Paired-sample, one-tailed t-tests were performed to compare the mean percentage-based deviations (biases) associated with the four forecasting methods. The null hypothesis in each instance was that the means were equal, tested against an alternative hypothesis of non-equality. Stated formally,

$$H_{01}: \mu_{A(AB)} = \mu_{B(AB)} \quad \text{vs.} \quad H_{A1}: \mu_{A(AB)} > \mu_{B(AB)}$$

$$H_{02}: \mu_{A(AC)} = \mu_{C(AC)} \quad \text{vs.} \quad H_{A2}: \mu_{A(AC)} > \mu_{C(AC)}$$

$$H_{03}: \mu_{A(ABCD)} = \mu_{B(ABCD)} \quad \text{vs.} \quad H_{A3}: \mu_{A(ABCD)} > \mu_{B(ABCD)}$$

$$H_{04}: \mu_{A(ABCD)} = \mu_{C(ABCD)} \quad \text{vs.} \quad H_{A4}: \mu_{A(ABCD)} > \mu_{C(ABCD)}$$

$$H_{05}: \mu_{A(ABCD)} = \mu_{D(ABCD)} \quad \text{vs.} \quad H_{A5}: \mu_{A(ABCD)} > \mu_{D(ABCD)}$$

$$H_{06}: \mu_{B(ABCD)} = \mu_{C(ABCD)} \quad \text{vs.} \quad H_{A6}: \mu_{B(ABCD)} > \mu_{C(ABCD)}$$

$$H_{07}: \mu_{B(ABCD)} = \mu_{D(ABCD)} \quad \text{vs.} \quad H_{A7}: \mu_{B(ABCD)} > \mu_{D(ABCD)}$$

$$H_{08}: \mu_{C(ABCD)} = \mu_{D(ABCD)} \quad \text{vs.} \quad H_{A8}: \mu_{C(ABCD)} > \mu_{D(ABCD)}$$

where μ_A, μ_B, μ_C, and μ_D represent respectively the biases under the four forecasting methods, with the tests based on samples from the subfiles compared in combinations (AB), (AC), or (ABCD), as indicated. A 5% rejection criterion was predetermined. Acceptance of any alternative hypothesis would indicate that the second model performed significantly better than the first model with which it was being compared. Prior to performing the t-tests, it was anticipated that each alternative model would be significantly better than model A, that C and D would be better than B, and that D would be the best overall.

Models and Variables

For convenience of reference, the models and variables used in the course of performing the present research are summarized here. The classical (or traditional) power form model of learning or experience attributed to Wright

$$Y_A = B_0 \, X_1^{B_1} \tag{16}$$

and its logarithmic transformation

$$\ln Y_A = \ln B_0 + B_1 \ln X_1 \tag{25}$$

were used most extensively (Issues 1, 2, 5, 6, and 7). The modified power form model of learning attributed to Crawford

$$Y_U = B_0 \, X_1^{B_1} \tag{17}$$

and its logarithmic transformation

$$\ln Y_U = \ln B_0 + B_1 \ln X_1 \tag{26}$$

were used only in conjunction with the analysis of Issue 1. A variant of the classical power form model and of the Stanford-B equation

$$Y_A = B_0 \, (X_1 + C)^{B_1} \tag{18}$$

and its logarithmic transformation

$$\ln Y_A = \ln B_0 + B_1 \ln (X_1 + C) \tag{19}$$

were similarly used only in one analysis, that of Issue 3.

A multiplicative variant of the classical power form model (similar in form to Levenson's model)

$$Y_A = B_0 \, X_1^{B_1} \, X_2^{B_2} \, X_3^{B_3} \, X_4^{B_4} \, X_5^{B_5} \, X_6^{B_6} \tag{20}$$

and its logarithmic transformation

$$\ln Y_A = \ln B_0 + B_1 \ln X_1 + B_2 \ln X_2 + B_3 \ln X_3 +$$
$$B_4 \ln X_4 + B_5 \ln X_5 + B_6 \ln X_6 \qquad (21)$$

were introduced and used for the investigation of Issues 4 and 7. This model is considered to have particular merit for future extensions to other data bases.

The variables in the preceding equations are defined as follows:

Y_A = Cumulative Average Unit Price (or Cost)

Y_U = Unit Price (or Cost)

B_0 = Imputed First Unit Price (or Cost)

B_1 = Learning or Experience Slope Exponent

B_2 through B_6 = Modulation Effect Exponents

C = Implicit Prior Experience Quantity

X_1 = Cumulative Quantity

X_2 = Quantity Bought

X_3 = Maximum Delivery Rate

X_4 = Production Break Duration

X_5 = Delivery Lead Time

X_6 = Average Delivery Rate

The results achieved using the methodology just described are presented in Chapter VI.

CHAPTER V — DATA BASE DESCRIPTION

The procurement data base developed from proprietary Government sources to support the present research is described in this chapter. The subfile structure, referenced throughout the preceding chapter on research methodology and the following chapters on results and conclusions, is defined. Finally, the alternative inflation adjustments applied to the data base are explained.

Data Source

As indicated at the outset of this dissertation, avionics (aviation electronics) acquisitions were chosen to provide the data base for the present research for two related reasons. The first is the author's extensive prior knowledge of this area; the second is sponsorship of the research by the U.S. Air Force. To facilitate and expedite analysis, only Air Force procurements were considered, although some of this equipment was bought by the Air Force for delivery to and use by the Army, Navy, National Aeronautics and Space Administration, and allied governments. The avionics category was further restricted to include only navigation equipment and ultra-high-frequency radio transceivers (combined transmitters and receivers). This restriction was necessitated by limited data availability. Historical files on procurements of these particular equipment items were maintained past normal descruction dates due to unresolved legal disputes involving several major contractors.

To protect the proprietary interests of the contractors involved (as required by Federal law: 18 USC 1905), neither the specific equipment items investigated nor the responsible contractors are named in the dissertation. For the same reason, no detailed listing (i.e., contract dates, quantities, costs, prices, and production parameters) of the data base is provided. The actual data analyzed have not been distorted or disguised, though, and the author's academic advisory committee has been advised of the identities of the equipment items and their respective contractors. For reference purposes in the dissertation, equipment items and contractors are identified only as shown in Tables 11 and 12.

As is readily apparent from inspection of Table 12, several contractors have produced multiple items (most notably, contractors 6, 10, and 11). Similarly, several items have been produced by multiple contractors (most notably, items 7, 19, and 20). These particular contractors and items were not selected randomly, but rather by design, to permit comparisons of demonstrated experience both within and across firms.

Data elements collected include those shown in Table 13. Data were extracted directly from Government files by the author for all equipment items except 7, 16, 17, 18, 19, and 20. Data for those six items only were extracted from Appendix C to the 1975 Master of Science thesis of Blinn and Yri (Acquisition Management of Common Avionics in the United States Air Force).

For equipment items researched personally by the author, data elements 1 through 14 were extracted from official source documents

TABLE 11 — ITEM IDENTIFICATION

Item Number	General Description
1	Navigation Subsystem
2	Navigation Subsystem
3	Navigation Control
4	Radio Control
5	Radio Control
6	Radio Control
7	Radio Transceiver
8	Radio Transceiver
9	Radio Transceiver
10	Radio Transceiver
11	Radio Transceiver
12	Radio Transceiver
13	Navigation Subsystem
14	Navigation Subsystem
15	Navigation Subsystem
16	Navigation Subsystem
17	Navigation Subsystem
18	Navigation Subsystem
19	Navigation Subsystem
20	Navigation Subsystem

TABLE 12 – CONTRACTOR AND ITEM CROSS-REFERENCE

		Contractor												
		1	2	3	4	5	6	7	8	9	10	11	12	13
	1										X			
	2										X			
	3										X			
E	4						X							
Q	5											X		
U	6											X		
I	7*	X		X			X			X				
P	8						X							
M	9						X							
E	10											X		
N	11											X		
T	12											X		
	13										X			
I	14										X			
T	15										X			
E	16*		X											
M	17*								X				X	
	18*								X					
	19*				X	X	X	X						X
	20*				X	X	X	X						X

* Detailed cost and schedule data are not available for these items.

NOTE: X indicates contractor produced item on at least one contract.

TABLE 13 — DATA ELEMENTS COLLECTED

Element	Description
1	Item Identification
2	Contractor Identification
3	Purchase Date
4	Quantity Bought in Lot
5	Unit Price
6	Direct Labor Cost
7	Purchased Material Cost
8	Total Manufacturing Cost
9	Total Price for Lot
10	Delivery Schedule
11	Contract Type
12	Funds Source
13	Procuring Office
14	Identification of Competitors
15	Explanatory Comments

NOTE: Data elements 6, 7, 8, 10, and 14 were not available for equipment items 7, 16, 17, 18, 19, or 20.

contained in Government procurement files, including contractor proposals, Defense Contract Audit Agency reports, price negotiation memoranda, Defense Contract Administration Services and Air Force Plant Representative Office reports, contracts, and related correspondence. Explanatory comments (data element 15) were extracted from these same sources, augmented by personal and telephone conversations with Government procurement officers, program managers, and program engineers. For equipment items originally researched by Blinn and Yri, the same sources cited above were reportedly used. However, Blinn and Yri did not collect data elements 6, 7, 8, 10, and 14, as those elements were not essential to their research objectives.

Preparation for Analysis

For purposes of computer manipulation and analysis of the data elements collected, each set of data elements relating to a specific contractual action was identified as an individual case. Therefore, the number of cases analyzed corresponds directly to the number of separate purchases for each equipment item. For each of the 361 cases developed, the data elements shown in Table 14 were derived (insofar as possible) from the raw data collected, and were then compiled for computer processing. As noted in Tables 12 and 13, cost details and delivery schedules were not available for equipment items 7 and 16 through 20, so case data elements for those specific equipments were limited.

TABLE 14 — CASE DATA ELEMENTS INPUT TO COMPUTER

Data Element	Description
Contractor Identification	Per Table 7
Item Identification	Per Table 6
Purchase Month	Month Lot Bought
Purchase Year	Year Lot Bought
Quantity Bought	Number of Units in Lot
Unit Price	Dollars per Unit (Lot Average)
Unit Direct Labor Cost	Dollars per Unit (Lot Average)
Unit Purchased Material Cost	Dollars per Unit (Lot Average)
Unit Total Manufacturing Cost	Dollars per Unit (Lot Average)
Maximum Delivery Rate	Units per Month
Production Break Duration	Number of Months
Delivery Lead Time	Number of Months
Delivery Duration	Number of Months

Certain of the data items collected did not aid in discriminating amongst cases, and therefore were not coded for computer processing. Since all purchase actions reviewed involved fixed price (rather than cost type) contracts, Contract Type was not coded. Since the Funds Source was invariably from production (as contrasted with research and development or operations and maintenance) accounts, that element was not coded. In view of the lack of discriminating data, no hypotheses involving Contract Type or Funds Source variables are set forth. Finally, the Procuring Office and the Identification of Competitors elements were combined with Explanatory Comments; none of these three elements were coded, as they were not required for quantitative analyses.

Four data files were generated, reflecting four alternative treatments for the effects of inflation, as described in the next section. Each of these four files was further divided into 32 subfiles, as shown in Table 15. These subfiles will be referred to frequently in the presentation of results in Chapter VI. Subfiles were generated only when two or more procurements of an equipment item were made from one contractor or grouping of contractors. Note that contractor code ALL reflects an industry composite (grouping of contractors) for a particular equipment item, and not a specific contractor. Since these industry composite subfiles (i.e., those involving groupings of contractors) contain all of the procurement cases for a particular equipment item, they can include single cases which are not reflected in other individual subfiles.

TABLE 15 — SUBFILE STRUCTURE

Subfile	Item Type	Contractor	No. of Cases
1	1	10	35
2	2	10	16
3	3	10	31
4	4	6	23
5	5	11	7
6	6	11	3
7	7	1	7
8	7	3	4
9	7	6	7
10	7	ALL*	19
11	8	6	19
12	9	6	9
13	10	11	18
14	11	11	3
15	12	11	5
16	13	10	21
17	14	10	31
18	15	10	33
19	16	2	18
20	17	8	18
21	17	12	2
22	17	ALL*	20
23	18	8	17
24	19	5	3
25	19	6	7
26	19	13	5
27	19	ALL*	17
28	20	5	4
29	20	6	7
30	20	7	2
31	20	13	6
32	20	ALL*	20

* Industry composite; see text.

Inflation Adjustments

To minimize inflation effects, all price and cost dollar inputs were adjusted using implicit deflators. Except as otherwise noted, these deflators were calculated based on Federal Purchases of Goods and Services (FPGS) indices, obtained from various issues of the Survey of Current Business. The year 1975 was selected as the base year, since it is the most recent period for which the FPGS and Gross National Product (GNP) indices have been firmly established.

One aspect of the present research entailed comparing the results of analyses obtained using FPGS deflators with the results obtained under three other treatments. These other treatments involved: 1) Ignoring inflation (making no adjustments to then-year dollar figures), 2) Using deflators calculated based on GNP indices (also obtained from the Survey of Current Business), and 3) Using avionics procurement deflators developed by Air Force financial analysts (Aeronautical Systems Division, 1976). For reference purposes, the inflation adjustment factors used are presented in Appendix B.

CHAPTER VI — RESULTS OF ANALYSIS

The results obtained from the empirical research investigations outlined in the preceding chapters are described and discussed here. Following the format already established, each research issue will be examined in turn in subsequent sections of this chapter. Since over 5000 pages of computer products were generated in the course of the analyses, only summary results reflecting the most important and pertinent findings are being reported. For general reference purposes, the cumulative average theory price experience curves corresponding to each of the 32 avionics data subfiles generated for the present research are reproduced in Appendix C; all dollar values graphed were adjusted using Federal Purchases of Goods and Services (FPGS) deflators.

All price experience subfile regressions based on FPGS deflated data were found to be significant at least at the 5% level, and 84% of them were significant at the 1% level or better. These significance tests confirm that the values of the regression parameters, representing the imputed first unit cost intercept and the experience slope exponent, are significantly different from zero.

Experience Vs. Learning

Issue 1: How do experience curves differ from traditional learning curves in the Government procurement environment? Recall from Chapter IV that the first aspect of this issue to be investigated was

the question of the extent to which price follows cost in the unique environment of the military market place. Since price experience curves may be viewed as an approximation to the summation of a whole set of underlying component learning curves, this question was approached by comparing price experience slopes with learning slopes for direct labor costs, purchased material costs, and total manufacturing costs. A secondary aspect of this issue was the question of the relative merits of cumulative average theory and unit theory in experience effect analyses. The findings will be briefly stated, then supported.

It was found that prices usually closely follow costs even under Government procurement conditions. This finding suggests that experience effect theories should be applicable in Government procurements as well as in consumer and industrial product markets, even though Government interventions and controls tend to restrict contractors' flexibility. As an example, consider the performance of Contractor 6 on Item 4. Figures 6 through 9 depict the costs and prices of that procurement sequence, determined using cumulative average theory. (In the computer generated plots appearing hereafter, asterisks represent individual plot points. Digits appearing in lieu of asterisks, such as "2" or "4" in Figure 6, represent the number of plot points overlaid at one location due to insufficient graphic resolution.) The typically substantial extent of smoothing resulting from the cumulative average theory is readily apparent when these four figures are compared with Figures 10 through 13, which depict the same procurement sequence but reflect unit theory. Since the

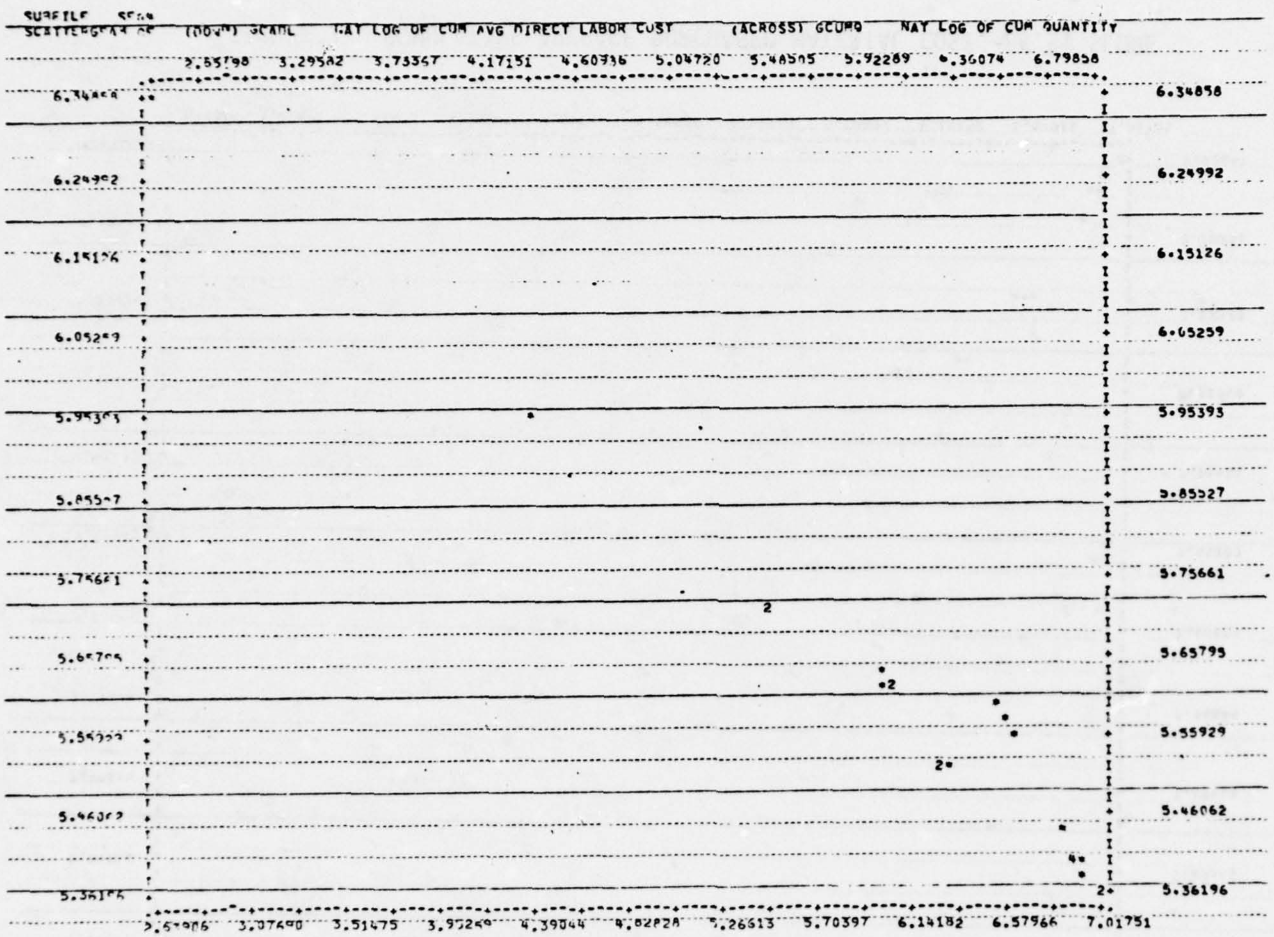


FIGURE 6 — CUMULATIVE AVERAGE DIRECT LABOR COST, 86.1% SLOPE

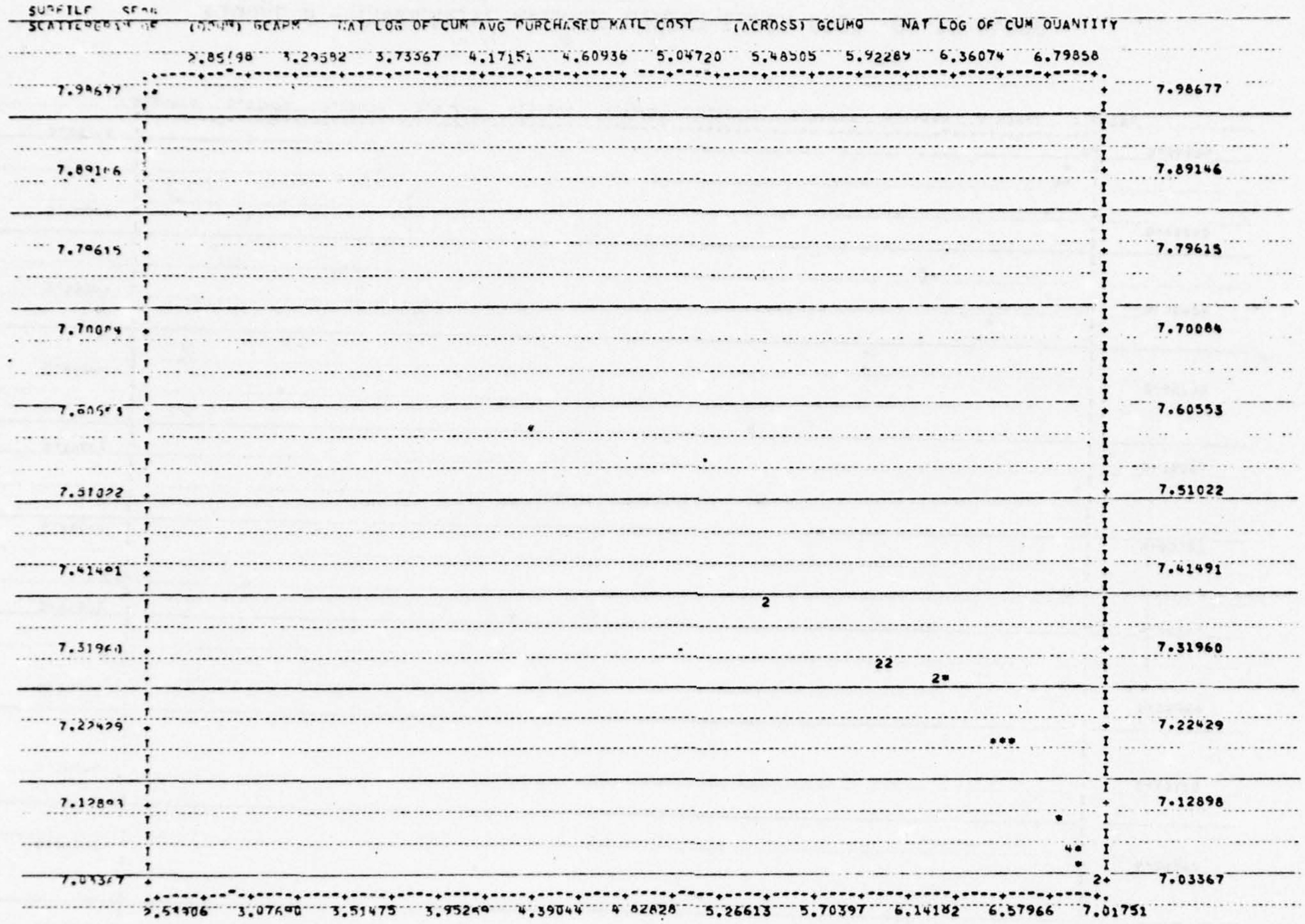


FIGURE 7 — CUMULATIVE AVERAGE PURCHASED MATERIAL COST, 86.5% SLOPE

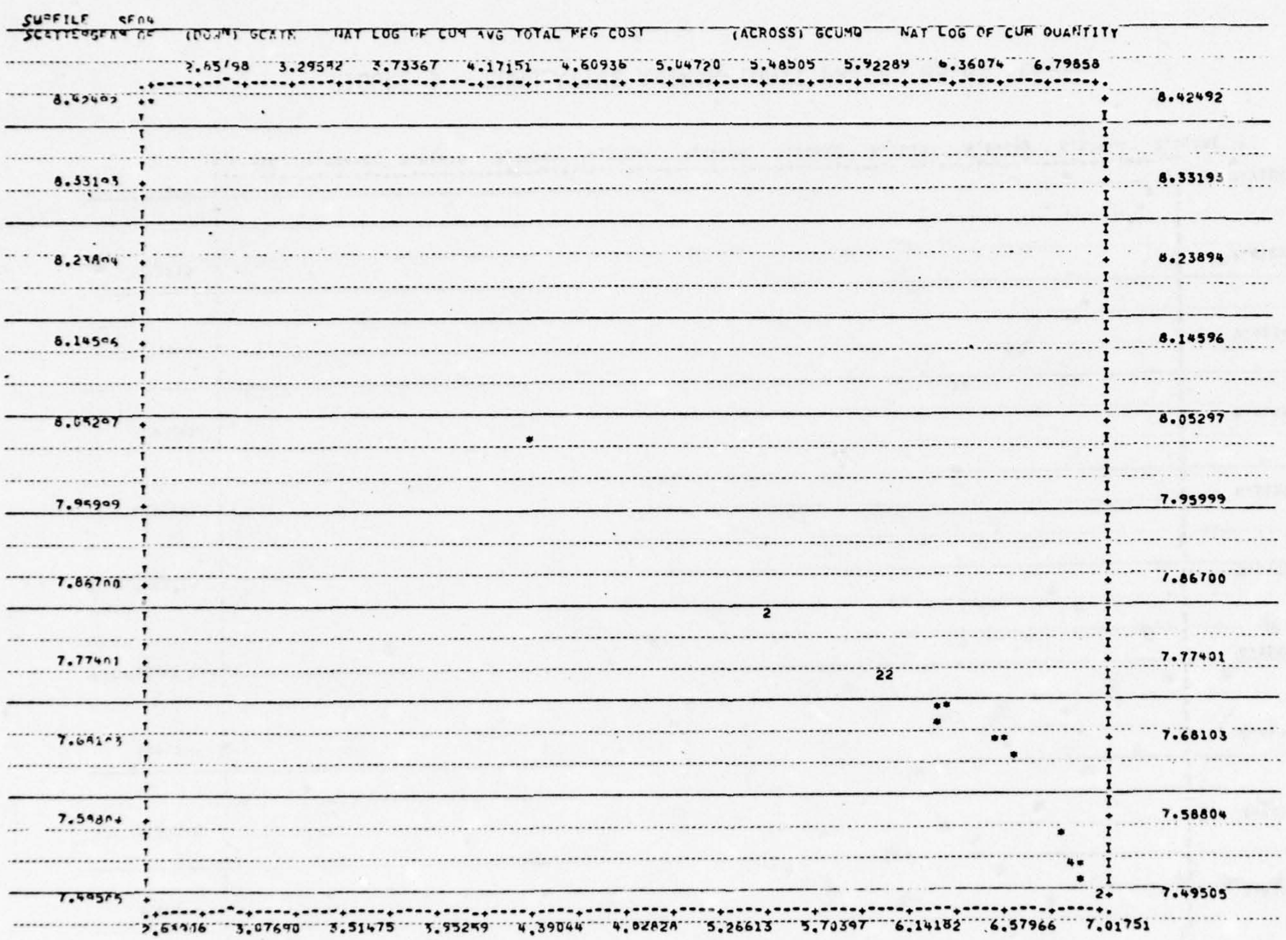


FIGURE 8 — CUMULATIVE AVERAGE TOTAL MANUFACTURING COST, 86.8% SLOPE

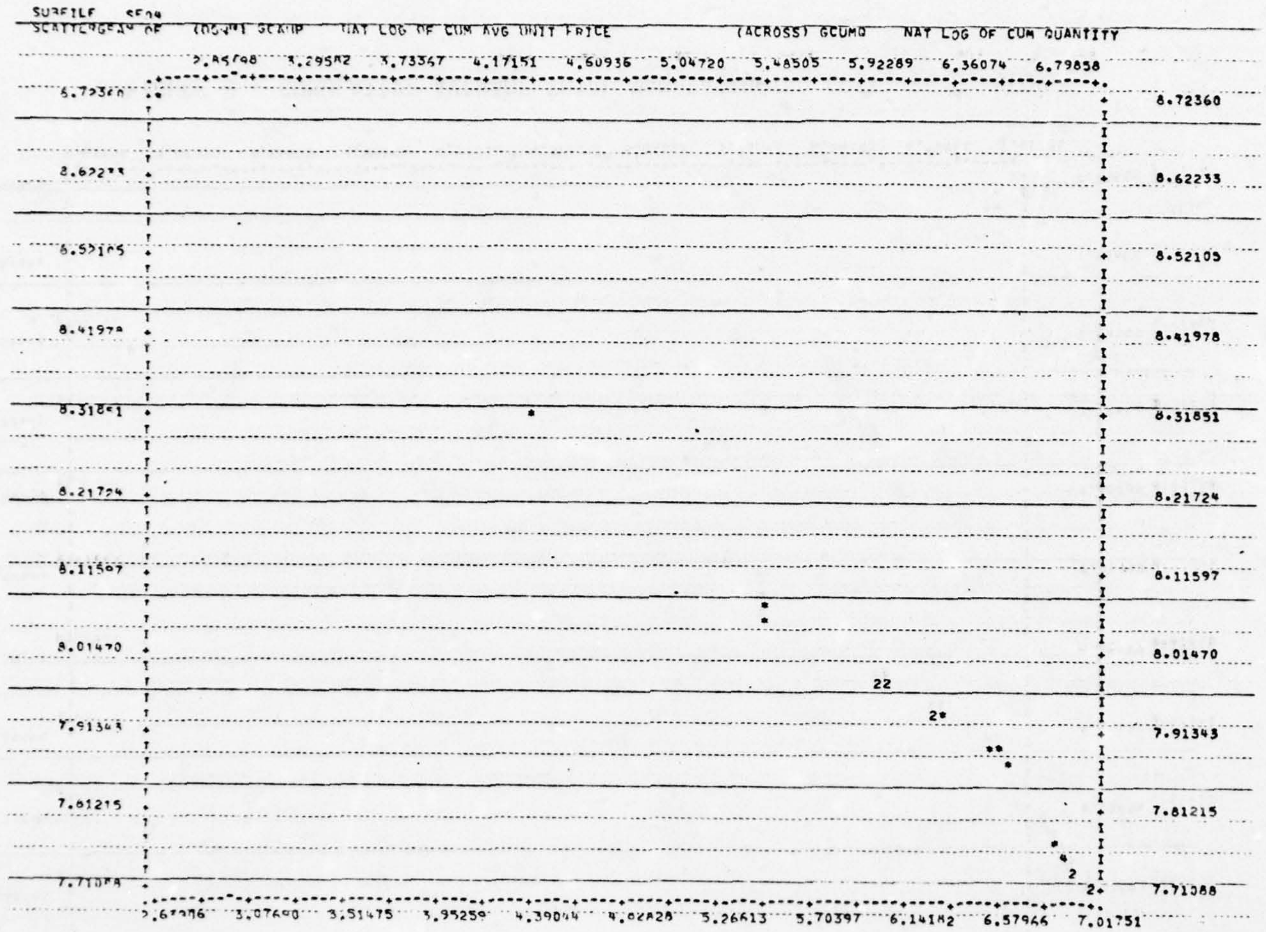


FIGURE 9 — CUMULATIVE AVERAGE UNIT PRICE, 85.4% SLOPE

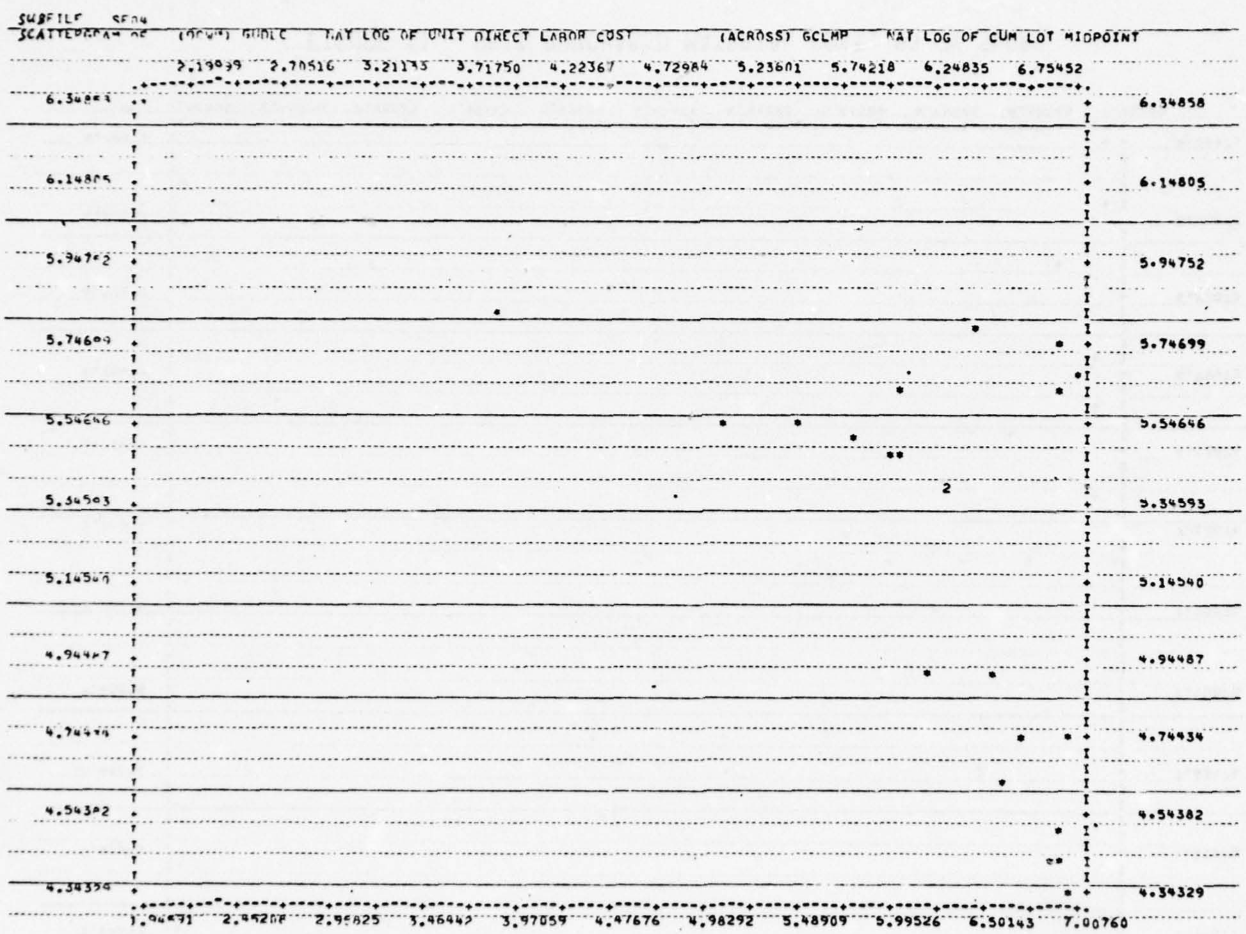


FIGURE 10 — UNIT DIRECT LABOR COST, 81.3% SLOPE

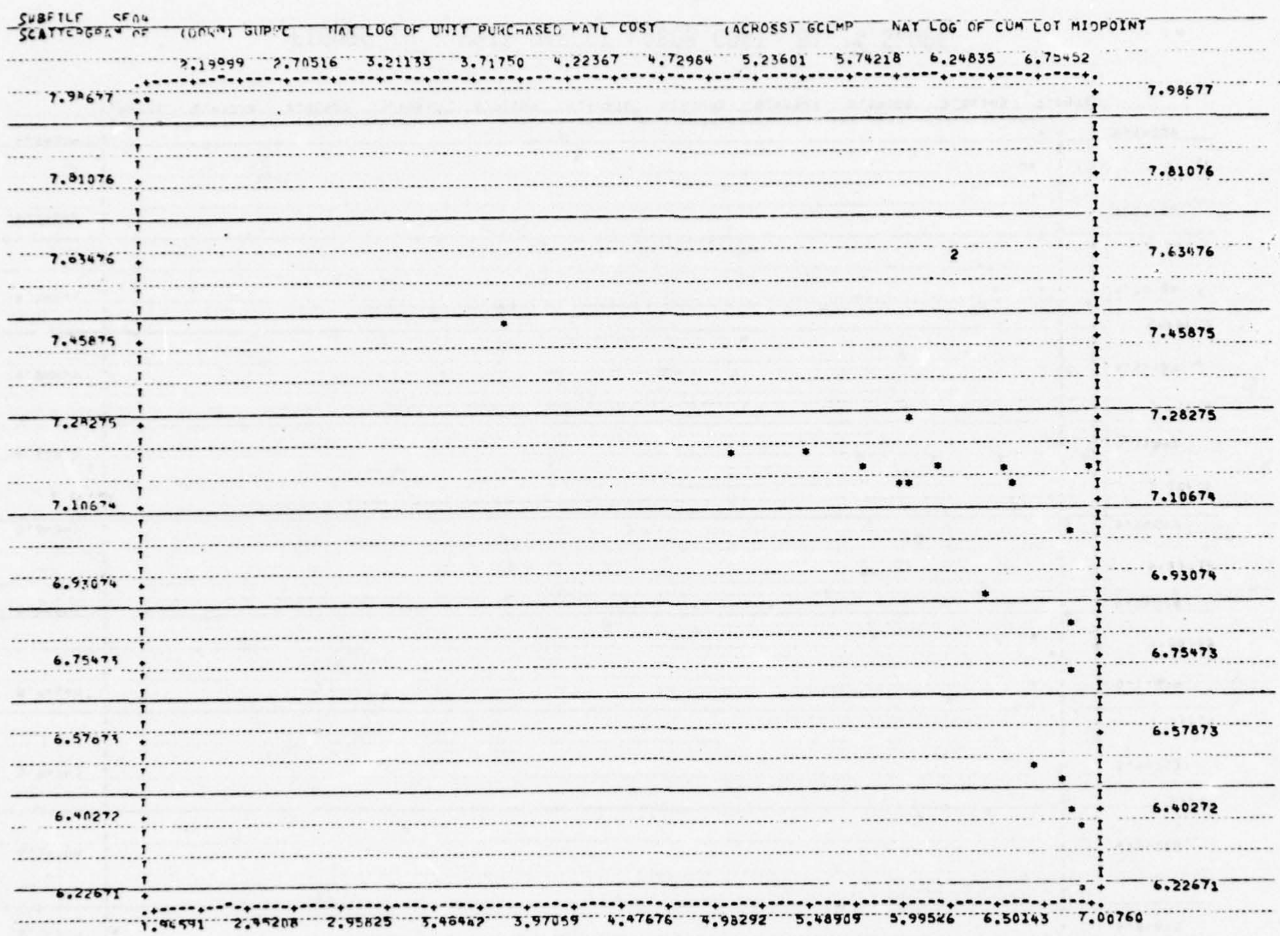


FIGURE 11 — UNIT PURCHASED MATERIAL COST, 83.7% SLOPE

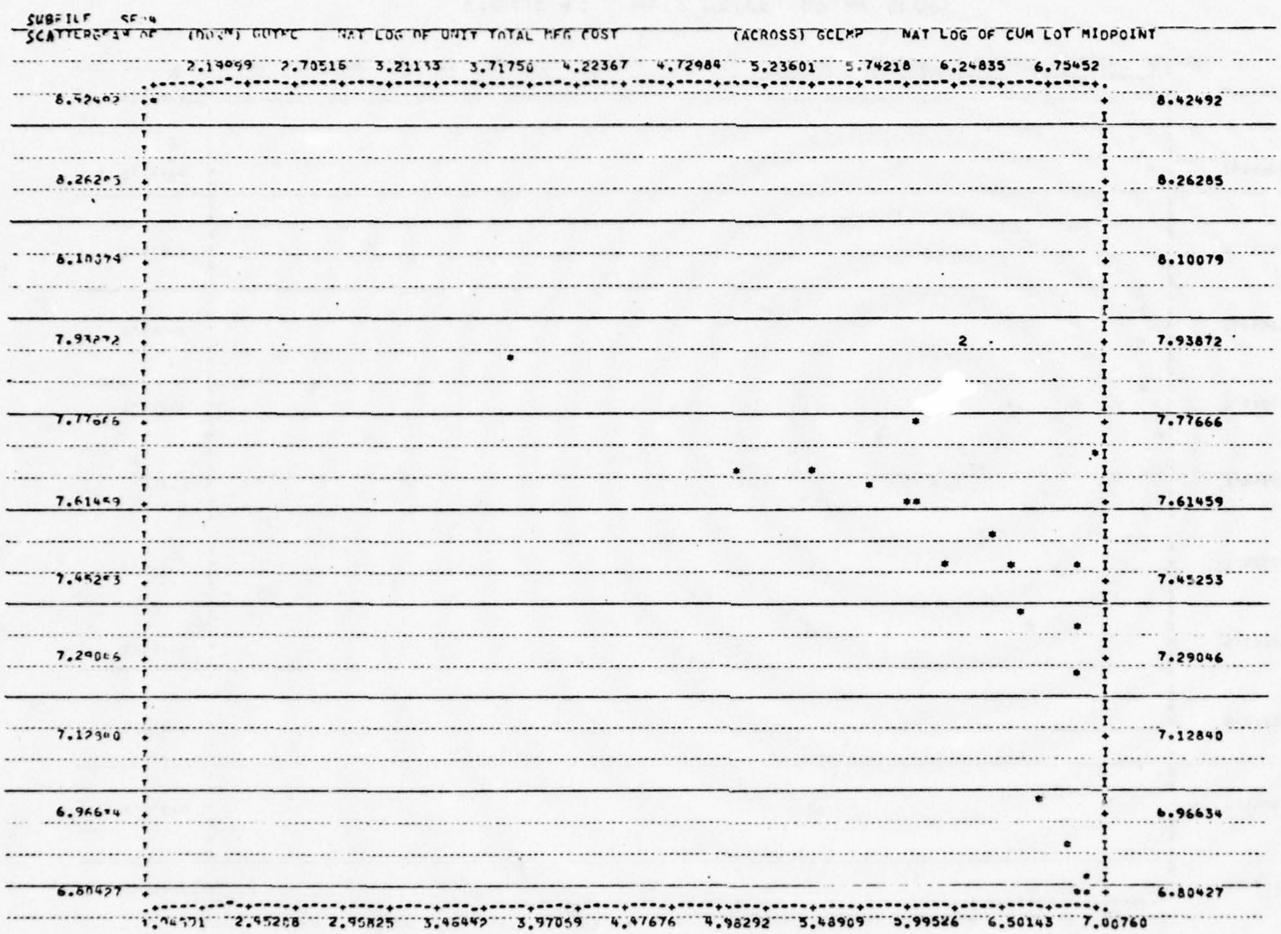


FIGURE 12 – UNIT TOTAL MANUFACTURING COST, 84.0% SLOPE

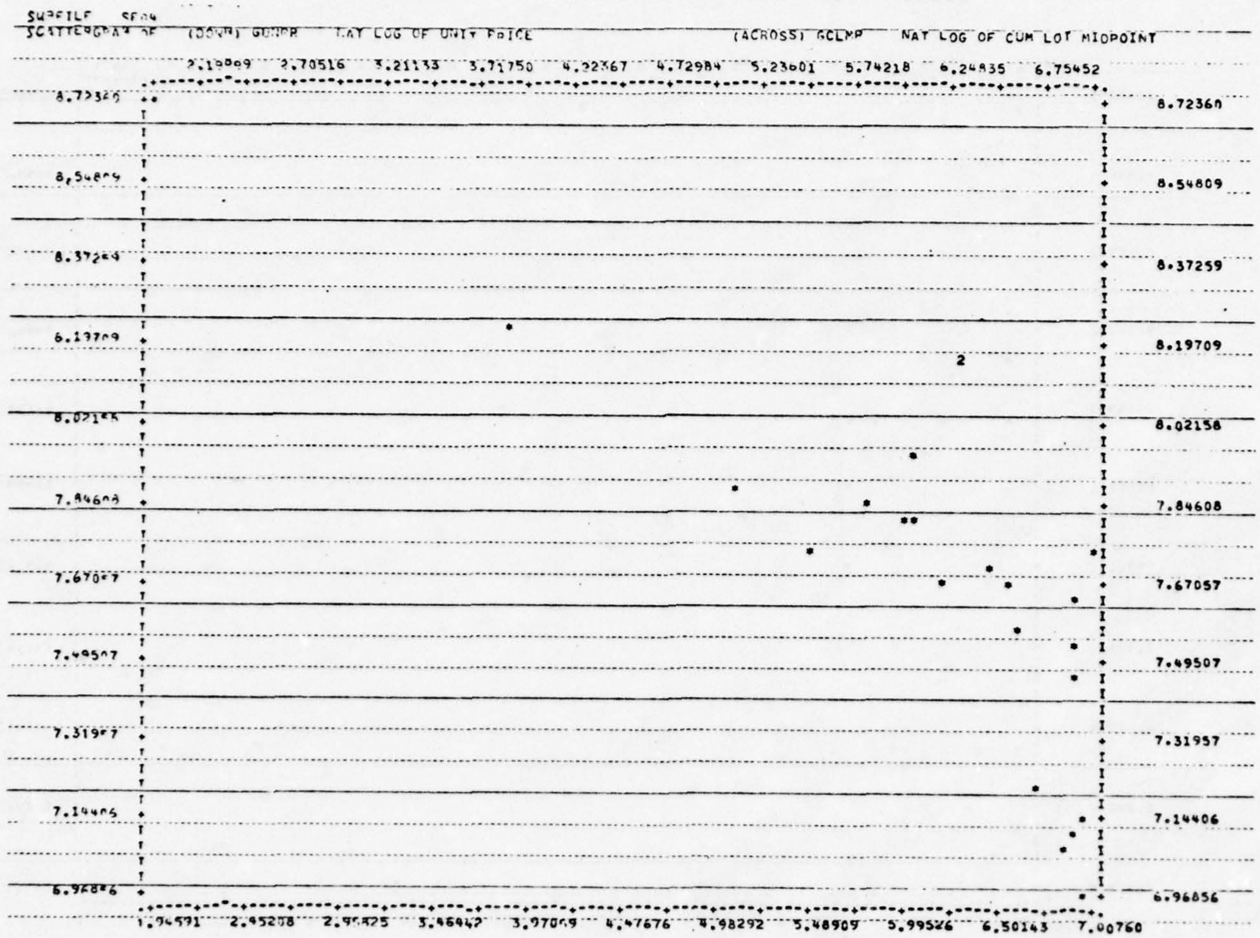


FIGURE 13 — UNIT PRICE, 82.8% SLOPE

experience curve theory emphasis is on planning and prediction, rather than on control, this smoothing effect is not only acceptable, it is even desirable.

From regression slope comparisons under cumulative average theory (see Table 16), it is evident that mean price experience slope is most closely aligned with mean total manufacturing cost slope for Contractors 6 and 10. However, for Contractor 11, mean price experience slope is most closely aligned with mean direct labor cost, and for the sub-industry composite of all three contractors, mean price experience slope is most closely aligned with mean purchased material cost. Under unit theory (see Table 17), mean price experience slope is most closely aligned with mean purchased material cost for each contractor and for the sub-industry composite. (For reference purposes, tables of observed regression slopes, coefficients of determination, and significance levels are presented in Appendix D.) This variety of alignments of price with various cost components underscores the uniqueness of individual contractor learning and experience patterns and pricing policies.

An indication of the extent of the differences amongst contractors, and thus of the inappropriateness of relying on "industry average" curve slopes, is given by the results of attempts to predict price experience curve slopes as additive functions of the direct labor, purchased material, and total manufacturing cost curve slopes, using multivariate regression techniques (see Table 18). For each individual contractor, a moderately significant predictive relationship was determined; however, there is no consistency from one contractor to

TABLE 16 — REGRESSION SLOPE COMPARISONS, CUMULATIVE AVERAGE THEORY

	Contractor			
	6	10	11	6 & 10 & 11
DIRECT LABOR COST				
MIN	.861	.760	.802	.760
MAX	1.003	.858	.968	1.003
MEAN	.938	.807	.906	.870
STD DEV	.072	.046	.073	.082
PURCHASED MATERIAL COST				
MIN	.865	.850	.842	.842
MAX	1.007	.991	.954	1.007
MEAN	.943	.919	.905	.919
STD DEV	.072	.057	.054	.056
TOTAL MANUFACTURING COST				
MIN	.868	.814	.816	.814
MAX	1.034	.915	.868	1.034
MEAN	.927	.876	.837	.873
STD DEV	.093	.043	.022	.058
PRICE				
MIN	.854	.831	.827	.827
MAX	1.046	.955	1.054	1.054
MEAN	.924	.893	.926	.911
STD DEV	.106	.047	.103	.078

TABLE 17 — REGRESSION SLOPE COMPARISONS, UNIT THEORY

	Contractor 6	10	11	6 & 10 & 11
		DIRECT LABOR COST		
MIN	.813	.451	.761	.451
MAX	.995	.638	.969	.995
MEAN	.933	.536	.883	.745
STD DEV	.104	.071	.094	.205
		PURCHASED MATERIAL COST		
MIN	.837	.730	.779	.730
MAX	.957	.933	.953	.957
MEAN	.892	.841	.886	.868
STD DEV	.061	.089	.072	.076
		TOTAL MANUFACTURING COST		
MIN	.840	.700	.785	.700
MAX	.972	.777	.878	.972
MEAN	.889	.747	.814	.801
STD DEV	.073	.033	.038	.070
		PRICE		
MIN	.828	.822	.795	.795
MAX	1.023	.927	1.059	1.059
MEAN	.906	.878	.907	.895
STD DEV	.103	.041	.112	.080

TABLE 18 — PRICE EXPERIENCE CURVE SLOPE PREDICTIONS

Contractor	Constant	Coefficients			Adjusted R^2	Signif.
		Labor Slope	Material Slope	Tot. Mfg. Slope		
CUMULATIVE AVERAGE THEORY						
6	-.131	-	-	+1.138	.998	.020
10	+1.005	+1.292	+1.347	-2.730	.967	.020
11	+.920	-1.510	-	+1.642	.962	.019
6 & 10 & 11	+.753	-	-.707	+.927	.103	.219
UNIT THEORY						
6	-.347	-	-	+1.410	.985	.055
10	+.330	+.252	+.491	-	.816	.037
11	+.930	-1.273	-	+1.353	.983	.009
6 & 10 & 11	+.297	-.212	-	+.943	.196	.120
	B_0	B_1	B_2	B_3		

$$(\text{Price Slope}) = B_0 + B_1 (\text{Labor Slope}) + B_2 (\text{Material Slope}) + B_3 (\text{Tot. Mfg. Slope})$$

another (or from one theory to the other) with regard to the independent variables included or the signs of their coefficients. The differences in coefficient magnitudes and signs are attributed to different mixes of labor, material, and overhead costs. The relationships identified at the sub-industry composite level are not significant (5% criterion). These results suggest that individual contractors may be able to predict their own price experience slopes based on known or predicted slopes for their direct labor, purchased material, and total manufacturing cost curves. However, there is little likelihood of accurate price experience slope prediction based solely on industry averages for component cost slopes.

The results of paired-sample, two-tailed t-tests, performed to compare the sample means of product price experience curve slopes with those of direct labor, purchased material, and total manufacturing cost learning curve slopes, are presented in Table 19. For the subfiles examined, the null hypothesis of essentially parallel price and cost slopes could be rejected (5% criterion) under cumulative average theory only in one instance, the comparison of price experience slope with direct labor cost learning slope for Contractor 10. Even under unit theory, the null hypothesis could be rejected in only four of twelve comparisons, involving both direct labor and total manufacturing cost slopes for Contractor 10 and for the sub-industry composite of Contractors 6, 10, and 11. These results indicate that price follows cost even in the military market place, with the cost classification most closely followed (i.e., labor, material, or total) being a

TABLE 19 – T-TESTS ON REGRESSION SLOPES,

PRICE VS. COST COMPARISONS

	Contractor 6	10	11	6 & 10 & 11
DF	2	5	4	13
CUMULATIVE AVERAGE THEORY, PRICE VS. DIRECT LABOR COST				
T	-.39	4.20**	.25	1.36
P	.731	.009	.815	.196
CUMULATIVE AVERAGE THEORY, PRICE VS. PURCHASED MATERIAL COST				
T	.53	-1.17	.29	-.30
P	.647	.294	.784	.770
CUMULATIVE AVERAGE THEORY, PRICE VS. TOTAL MANUFACTURING COST				
T	-.36	.70	1.87	1.79
P	.754	.516	.135	.097
UNIT THEORY, PRICE VS. DIRECT LABOR COST				
T	.55	9.98**	.27	2.59*
P	.636	.000	.803	.022
UNIT THEORY, PRICE VS. PURCHASED MATERIAL COST				
T	.53	1.60	.28	.96
P	.648	.170	.796	.352
UNIT THEORY, PRICE VS. TOTAL MANUFACTURING COST				
T	.97	12.84**	1.80	4.32**
P	.436	.000	.146	.001

T = Computed T Value

DF = Degrees of Freedom

P = Two-Tailed Probability

* Significant at 5% Criterion.

** Significant at 1% Criterion.

function of the contractor's labor, material, and overhead cost mix and pricing policies.

The results of paired-sample, one-tailed t-tests, performed to compare the regression slope sample means observed under the cumulative average theory with those observed under the unit theory, are presented in Table 20. For each contractor, the slopes observed for at least one accounting classification were found to be significantly different (5% criterion). At the sub-industry composite level of aggregation, enough differences existed between slopes measured under the two theories to justify rejecting the null hypotheses for all four accounting classifications. These results suggest that, on a selective basis, it may be reasonable to approximate a cumulative average theory slope by a unit theory slope (or vice versa), but that such approximations are likely to be appropriate only at the level of individual contractor accounts, not at the level of sub-industry aggregations.

Whereas two of the three contractors demonstrated mean cumulative average theory price experience slopes similar to their total manufacturing cost slopes, Contractor 11's mean slopes diverge conspicuously. As shown in Figure 14, the relatively gradual price experience slope permits a rapid increase with cumulative quantity in the funds available for general and administrative expenses, independent research and development, and profit. (The construction in Figure 14 of price equal to total manufacturing cost at unit one is arbitrary, selected to make it easier to see the divergence of the two slopes.)

In non-Government business, it would not be unusual for a contractor to set price even lower than total manufacturing costs

TABLE 20 — T-TESTS ON REGRESSION SLOPES,
THEORY COMPARISONS

	Contractor 6	10	11	6 & 10 & 11
DIRECT LABOR				
T	.16	12.78**	2.17*	3.42**
DF	2	5	4	13
P	.444	.000	.048	.003
PURCHASED MATERIAL				
T	3.84*	1.74	1.35	2.53*
DF	2	5	4	13
P	.031	.072	.125	.013
TOTAL MANUFACTURING				
T	3.19*	4.75**	1.85	3.90**
DF	2	5	4	13
P	.043	.003	.069	.001
PRICE				
T	2.62	2.17*	2.04	3.90**
DF	2	5	4	13
P	.060	.041	.055	.001

T = Computed T Value

DF = Degrees of Freedom

P = One-Tailed Probability

* Significant at 5% Criterion.

** Significant at 1% Criterion.

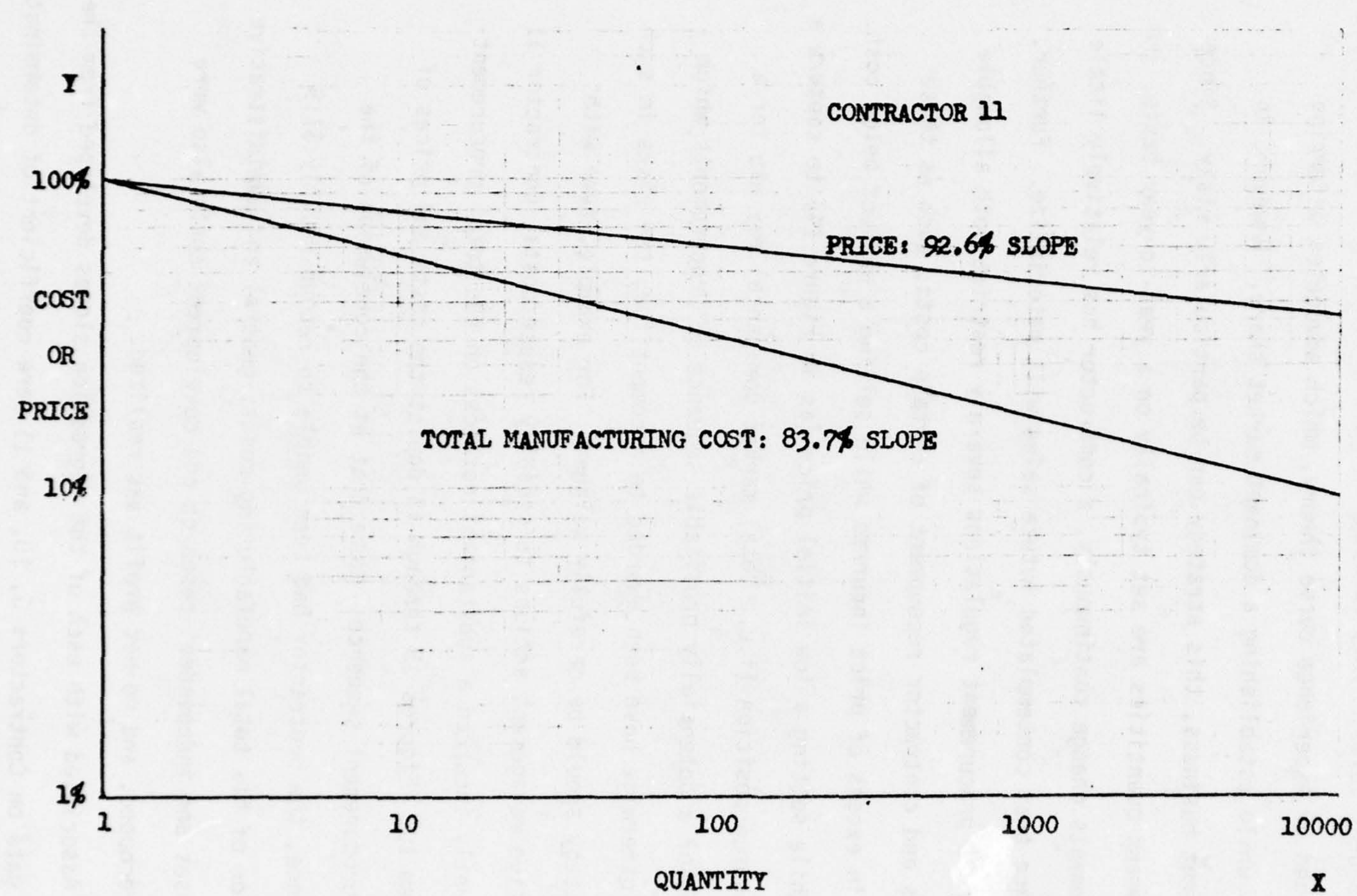


FIGURE 14 — DIVERGENCE OF SLOPES FOR TOTAL MANUFACTURING COST AND PRICE

initially, with the expectation of recovering his initial "investment" on subsequent sales. This strategy is completely consistent with and encouraged by experience curve theory, which advocates deferring profits while establishing a dominant market share. However, in Government business, this strategy can be particularly risky. Since procurement quantities are set typically on a year-to-year basis, and requirements change continuously, a contractor has relatively little assurance that contemplated future sales will materialize. Further, Government procurement regulations severely restrict both allowable profits and contractor recoupment of certain costs, such as those costs in excess of price incurred while selling a product below cost.

While setting a low initial price (as in Figure 14) to capture a sole-source position (i.e., total market dominance) may win for a contractor a potentially profitable sequence of procurements which might otherwise have been awarded to a competitor, the risks in such a strategy should be carefully weighed. For example, even with effective management actions to steadily reduce costs, Contractor 11 apparently incurred a substantial net loss on the total procurement of Item 10. Figures 15 through 18 depict the costs and prices of that procurement sequence. Note that at the conclusion of the sequence, the contractor had been unable to recoup roughly $1.9 million of his total manufacturing costs; general and administrative expenses and independent research and development costs also were not recouped, and no net profit was realized.

Associated with each of the regression slopes developed from the case data on Contractors 6, 10, and 11 were coefficient of determination

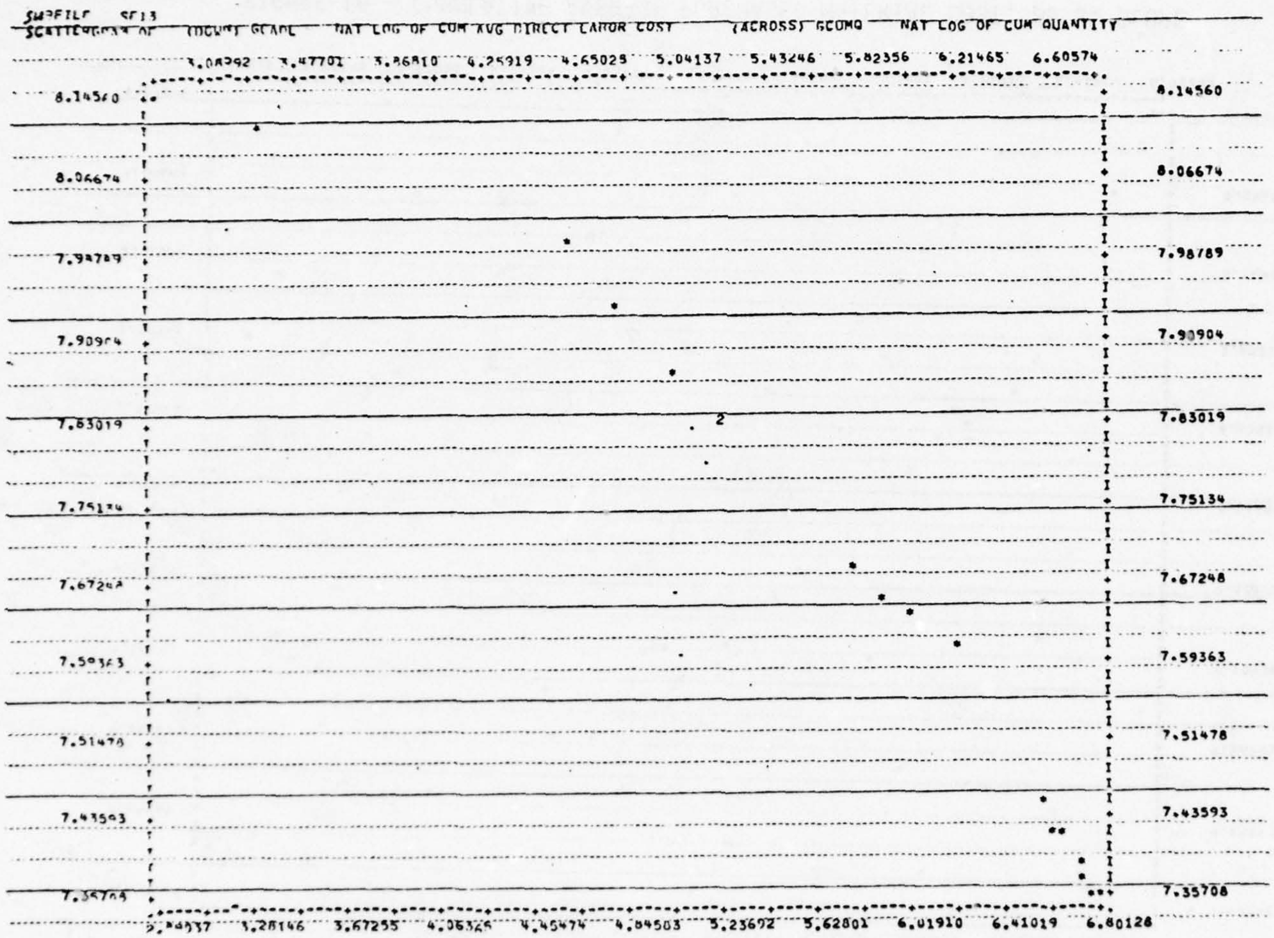


FIGURE 15 – CUMULATIVE AVERAGE DIRECT LABOR COST, 85.9% SLOPE

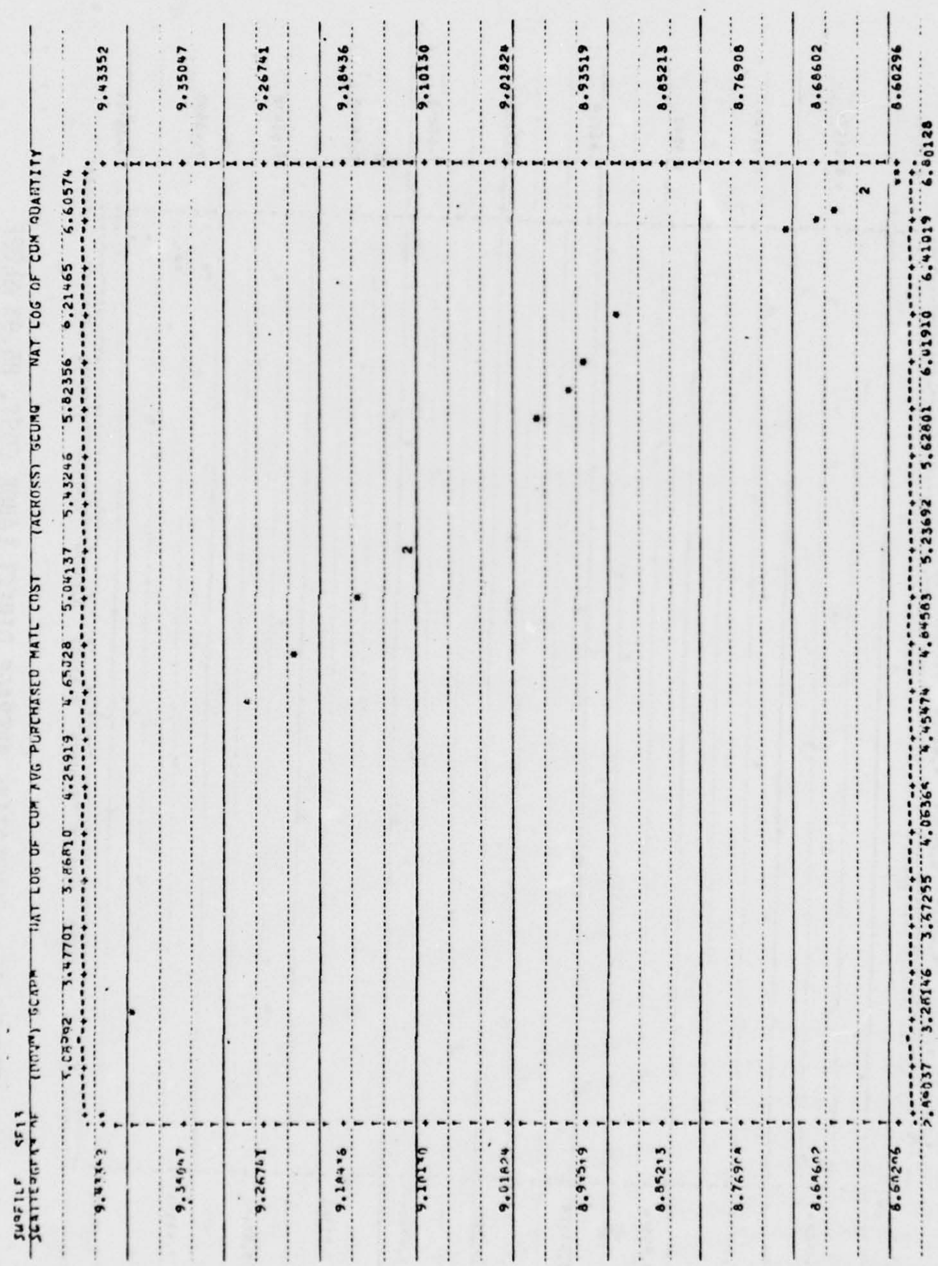


FIGURE 16 — CUMULATIVE AVERAGE PURCHASED MATERIAL COST, 85.3% SLOPE

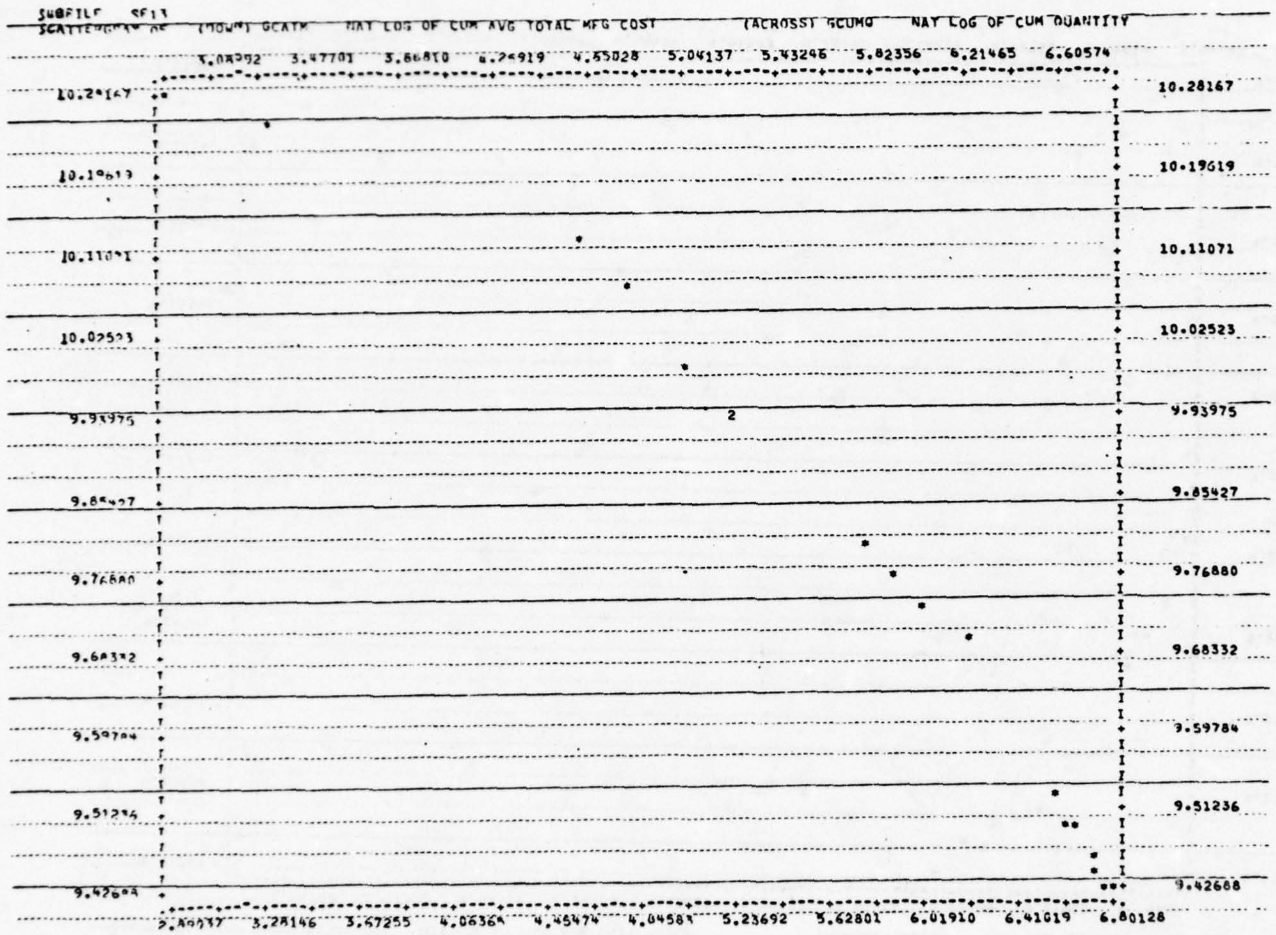


FIGURE 17 — CUMULATIVE AVERAGE TOTAL MANUFACTURING COST, 84.7% SLOPE

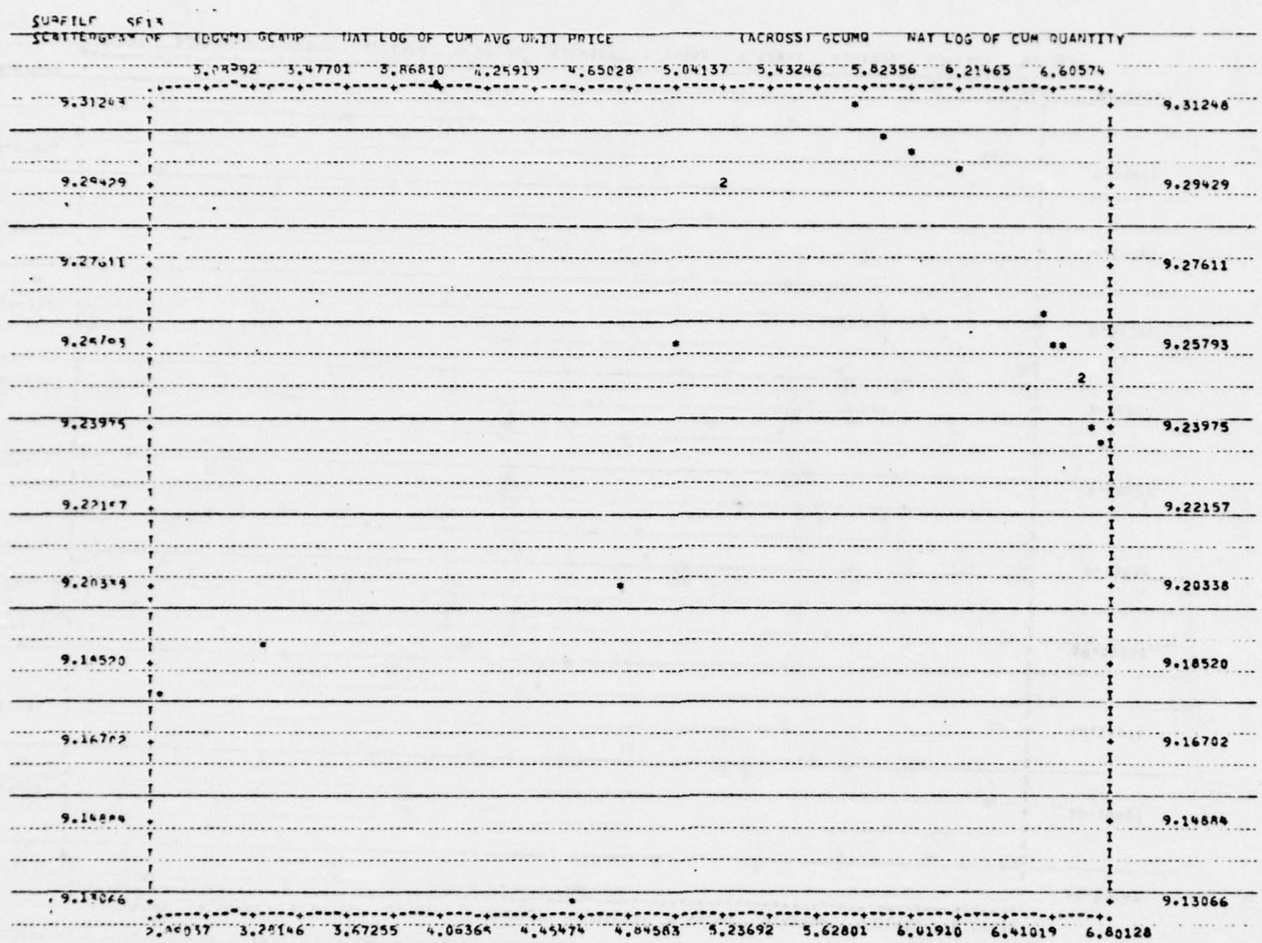


FIGURE 18 — CUMULATIVE AVERAGE UNIT PRICE, 101.6% SLOPE

(R^2) and significance level (F-test derived) values. These values are summarized in Tables 21 through 24. (The values observed for each case examined are listed in Appendix D.) For Contractors 6 and 10 and for the sub-industry composite, the highest mean R^2 values (and thus by implication the best fits of data and theory) were associated with price. For Contractor 11, the highest mean R^2 value was associated instead with total manufacturing cost, apparently due mainly to the risky pricing strategy depicted in Figures 17 and 18. The patterns of R^2 value relationships are the same under unit theory as under cumulative average theory. The observed R^2 values are consistently larger under the cumulative average theory, apparently due to the smoothing effect inherent in that theory.

Under cumulative average theory, the mean regression significance level is smallest (i.e., most significant) for all three contractors and for the sub-industry composite for the price experience curves. Additionally, for each population, the variance in significance level is minimum for the price experience curves. Under unit theory, however, there is no readily discernible pattern to the significance level comparisons. These findings suggest that cumulative average theory is preferable to unit theory for strategic planning projections. Further, under the traditional power form model of experience theory, prices conform more closely than costs.

In summary, price experience curves provide better statistical fits to procurement sequence data than do the underlying cost learning curves. Price experience curves generally parallel one or more component cost curves, particularly when determined using cumulative

TABLE 21 — REGRESSION COEFFICIENT OF DETERMINATION COMPARISONS, CUMULATIVE AVERAGE THEORY

	Contractor			
	6	10	11	6 & 10 & 11
DIRECT LABOR COST				
MIN	.019	.902	.807	.019
MAX	.967	.962	.995	.995
MEAN	.479	.930	.937	.836
STD DEV	.474	.027	.076	.272
PURCHASED MATERIAL COST				
MIN	.022	.333	.900	.022
MAX	.973	.981	.989	.989
MEAN	.498	.686	.938	.736
STD DEV	.475	.287	.038	.311
TOTAL MANUFACTURING COST				
MIN	.228	.765	.931	.228
MAX	.994	.967	.998	.998
MEAN	.733	.895	.976	.889
STD DEV	.437	.077	.026	.201
PRICE				
MIN	.773	.907	.289	.289
MAX	.997	.999	1.000	1.000
MEAN	.918	.970	.841	.913
STD DEV	.126	.035	.310	.190

TABLE 22 — REGRESSION COEFFICIENT OF DETERMINATION COMPARISONS, UNIT THEORY

	Contractor			
	6	10	11	6 & 10 & 11
		DIRECT LABOR COST		
MIN	.002	.275	.740	.002
MAX	.399	.717	.931	.931
MEAN	.135	.541	.845	.563
STD DEV	.228	.199	.072	.313
		PURCHASED MATERIAL COST		
MIN	.312	.028	.716	.028
MAX	.467	.724	.927	.927
MEAN	.408	.268	.821	.495
STD DEV	.083	.271	.085	.313
		TOTAL MANUFACTURING COST		
MIN	.101	.221	.778	.101
MAX	.704	.771	.979	.979
MEAN	.438	.432	.881	.593
STD DEV	.307	.233	.072	.294
		PRICE		
MIN	.052	.356	.067	.052
MAX	.770	.913	.999	.999
MEAN	.470	.668	.697	.636
STD DEV	.374	.239	.395	.316

TABLE 23 — REGRESSION SIGNIFICANCE LEVEL COMPARISONS, CUMULATIVE AVERAGE THEORY

	Contractor			
	6	10	11	6 & 10 & 11
DIRECT LABOR COST				
MIN	.000	.000	.000	.000
MAX	.361	.000	.145	.361
MEAN	.121	.000	.036	.039
STD DEV	.208	.000	.062	.100
PURCHASED MATERIAL COST				
MIN	.000	.000	.000	.000
MAX	.350	.000	.092	.350
MEAN	.117	.000	.026	.035
STD DEV	.202	.000	.039	.094
TOTAL MANUFACTURING COST				
MIN	.000	.000	.000	.000
MAX	.097	.000	.040	.097
MEAN	.032	.000	.011	.011
STD DEV	.056	.000	.017	.027
PRICE				
MIN	.000	.000	.000	.000
MAX	.000	.000	.028	.028
MEAN	.000	.000	.009	.003
STD DEV	.001	.000	.012	.008

TABLE 24 — REGRESSION SIGNIFICANCE LEVEL COMPARISONS, UNIT THEORY

	Contractor			
	6	10	11	6 & 10 & 11
DIRECT LABOR COST				
MIN	.001	.000	.000	.000
MAX	.438	.002	.170	.438
MEAN	.286	.000	.055	.081
STD DEV	.247	.001	.073	.155
PURCHASED MATERIAL COST				
MIN	.000	.000	.000	.000
MAX	.059	.207	.087	.207
MEAN	.020	.076	.048	.054
STD DEV	.034	.100	.052	.073
TOTAL MANUFACTURING COST				
MIN	.000	.000	.000	.000
MAX	.202	.024	.120	.202
MEAN	.067	.005	.036	.029
STD DEV	.116	.010	.051	.060
PRICE				
MIN	.000	.000	.002	.000
MAX	.278	.000	.151	.278
MEAN	.093	.000	.057	.040
STD DEV	.160	.000	.063	.082

average theory. Individual contractor learning and experience patterns and pricing policies are, however, unique. Indiscriminate reliance on industry average curve slopes is thus inappropriate. Divergent price experience curves and total manufacturing cost learning curves are indicative of a contractor's willingness to assume substantial risks in seeking potentially high profits. The most apparent difference between experience curves in Government and non-Government markets is in the typical experience slope steepness. In the Government market place, experience curve slopes were observed to typically range from 85% to 95%, as contrasted with the steeper 70% to 80% attributed to consumer and industrial markets.

Alternative Inflation Treatments

Issue 2: How are the forms of experience curves affected by alternative techniques for compensating for the effects of inflation? The four different treatments examined were:

A) Federal Purchases of Goods and Services (FPGS) Deflators,

B) Gross National Product (GNP) Deflators,

C) Avionics Procurement (AVPR) Deflators, and

D) Ignore Inflation.

The actual deflator values used are provided for reference in Appendix B. As can be seen from inspection of Figures 19 through 21, depicting subfile 03 as a representative procurement sequence, selection of alternative treatments for inflation typically has little effect on the general shape of the price experience curve, provided that inflation is not ignored entirely. However, when inflation is ignored, as in

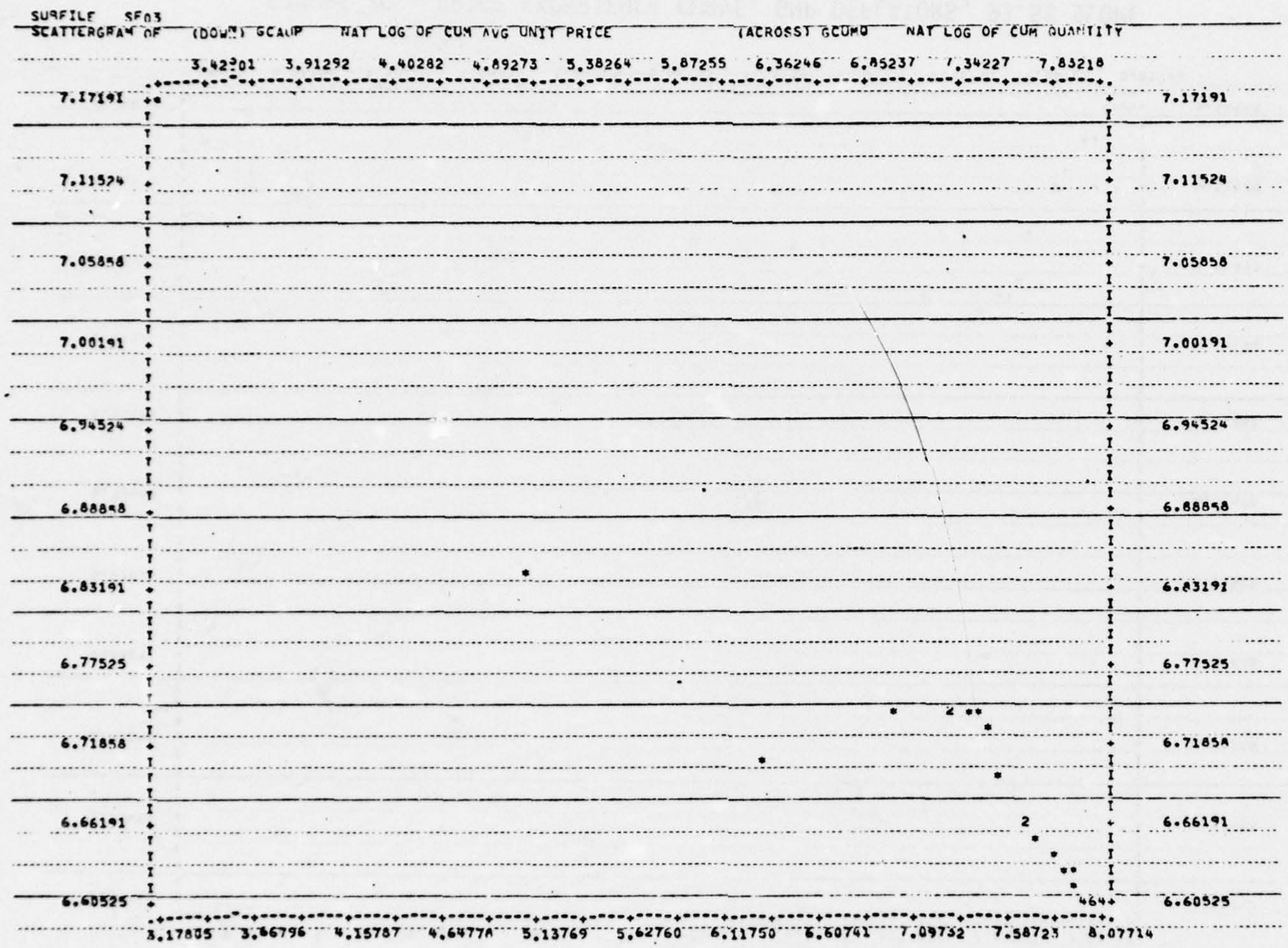


FIGURE 19 – PRICE EXPERIENCE CURVE, FPGS DEFLATORS, 93.0% SLOPE

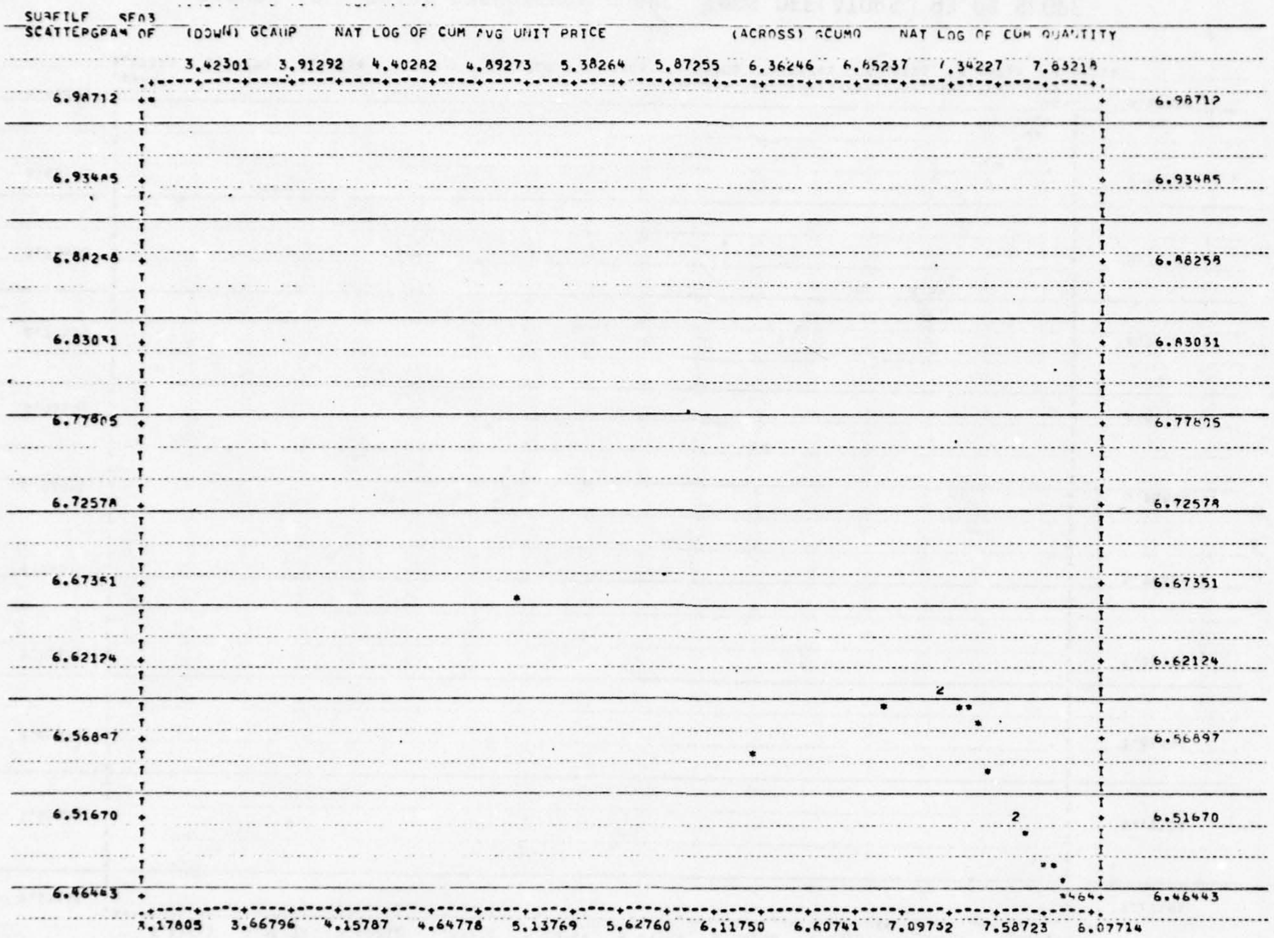


FIGURE 20 — PRICE EXPERIENCE CURVE, GNP DEFLATORS, 93.5% SLOPE

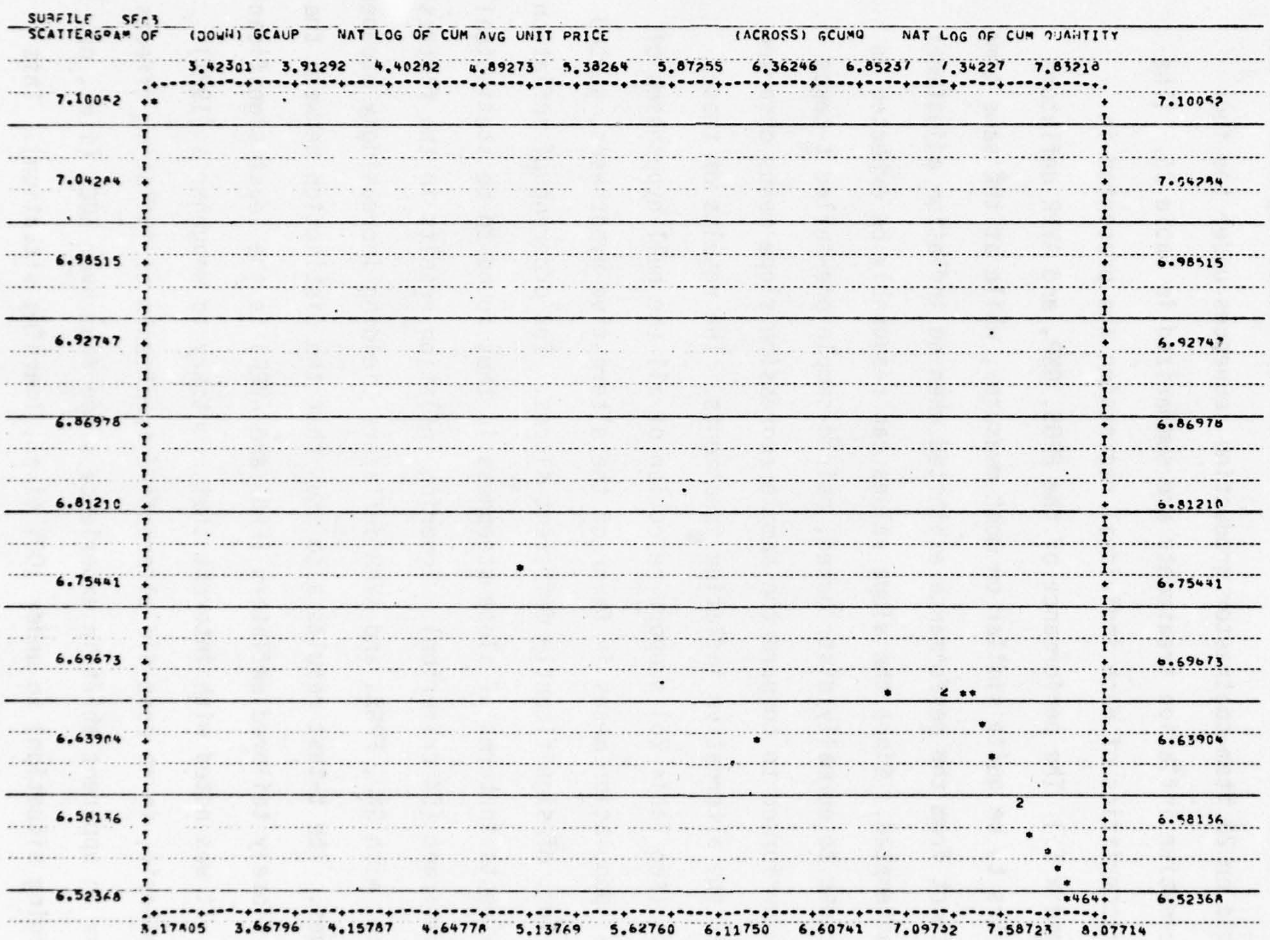


FIGURE 21 – PRICE EXPERIENCE CURVE, AVPR DEFLATORS, 92.8% SLOPE

Figure 22, price level shifts are emphasized and the trends which appear are more apt to be misleading.

The key characteristics of the price experience regressions performed on 28 item-contractor production sequences under the four alternative inflation treatments are summarized in Table 25. (The characteristics of each individual regression are presented in Appendix E.) The performance of the FPGS, GNP, and AVPR deflators appears to be quite similar on most measures, while at the same time distinct from the performance exhibited when no inflation adjustment is attempted. Since the slope values can reasonably be expected to be close to normally distributed, paired-sample one-tailed t-tests were performed to compare the sample regression slope means observed under the alternative inflation treatments. The results of these tests (see Table 26) support rejection of all the null hypotheses of equal population means in favor of the alternative hypotheses, stated earlier, of significantly different slopes. The ordering of inflation treatments in terms of slope steepness is thus found to be statistically significant (5% criterion). Ignoring inflation results in the flattest slope, with GNP, FPGS, and AVPR deflators yielding increasingly steeper slopes. The t-test results also show that the distinction between the two closely tailored deflators (FPGS and AVPR) is the least significant.

It was noted with interest that, contrary to Waggoner's (1971) hypothesis, in no case did alternative treatments of inflation effects cause an apparent shift in experience slope from over 100% (i.e., no learning situation) to under 100% (i.e., learning situation). This result is attributed to the makeup of the particular data analyzed,

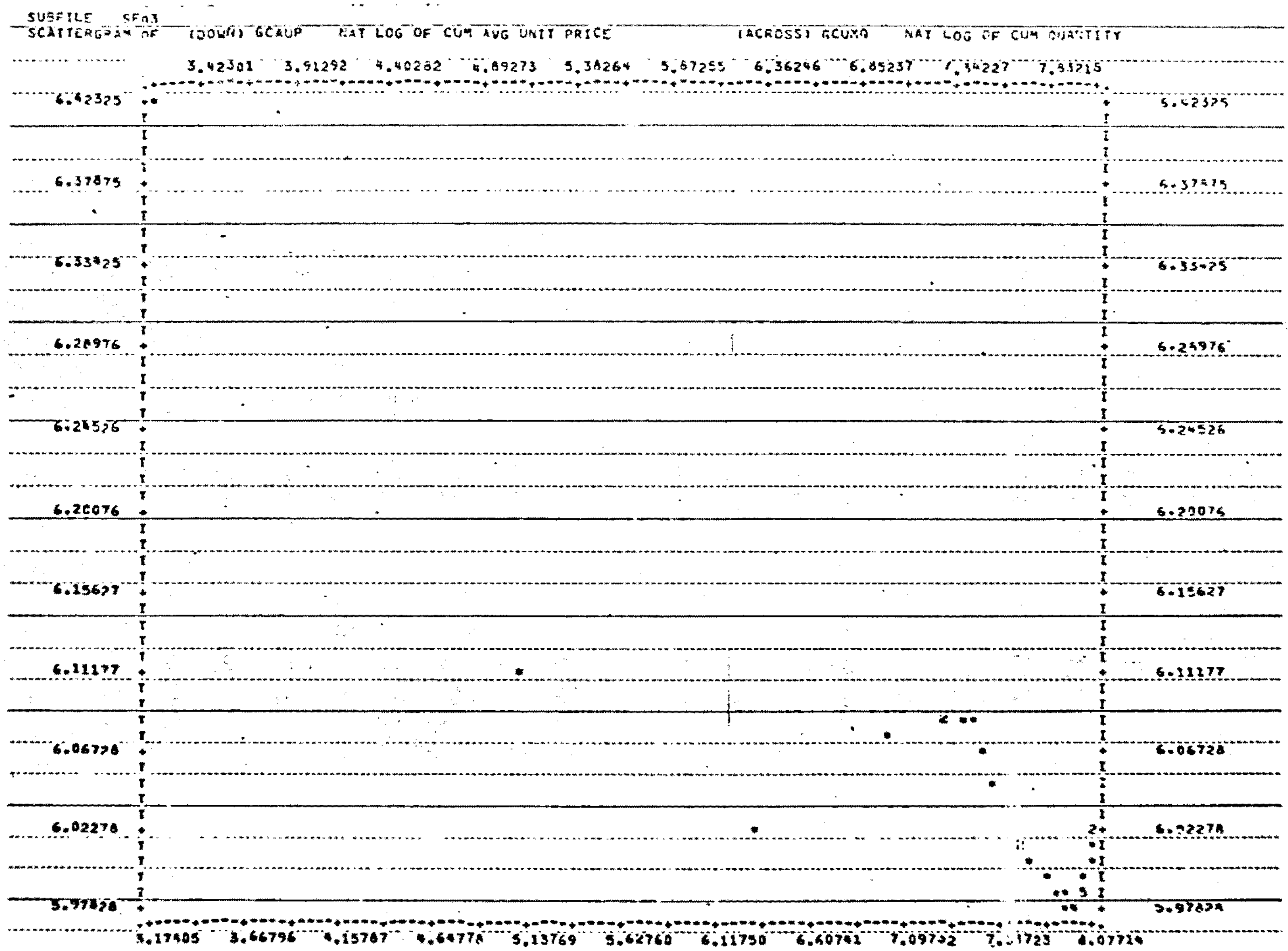


FIGURE 22 — PRICE EXPERIENCE CURVE, NO DEFLATORS, 95.0% SLOPE

TABLE 25 — INFLATION TREATMENT COMPARISONS

	Deflator			
	FPGS	GNP	AVPR	None
		SLOPE		
MIN	.82657	.83166	.82931	.84894
MAX	1.09644	1.09645	1.09645	1.12840
MEAN	.03162	.93692	.92847	.95863
STD DEV	.07778	.07795	.07853	.07914
		COEFFICIENT OF DETERMINATION		
MIN	.28944	.48930	.44905	.00040
MAX	1.00000	1.00000	1.00000	1.00000
MEAN	.90772	.92394	.92857	.86316
STD DEV	.16147	.13804	.12654	.22121
		SIGNIFICANCE		
MIN	.00001	.00001	.00001	.00001
MAX	.04935	.06094	.04164	.46870
MEAN	.00492	.00484	.00413	.02591
STD DEV	.01100	.01300	.00955	.09256
		STANDARD ERROR OF ESTIMATE		
MIN	.00074	.00074	.00074	.00074
MAX	.16050	.16481	.16427	.17261
MEAN	.02753	.02642	.02761	.03009
STD DEV	.03007	.03139	.03091	.03201

TABLE 26 — T-TESTS ON INFLATION TREATMENTS

	Deflators		
	GNP	AVPR	None
FPGS Deflators			
T	-5.86**	1.99*	-8.75**
DF	27	27	27
P	.000	.028	.000
GNP Deflators			
T		6.31**	-8.38**
DF	-	27	27
P		.000	.000
AVPR Deflators			
T			-9.09**
DF	-	-	27
P			.000

T = Computed T Value

DF = Degrees of Freedom

P = One-Tailed Probability

NOTE: Tests compared mean observed regression slopes.

* Significant at 5% Criterion.

** Significant at 1% Criterion.

however, and should not be construed as refuting Waggoner's hypothesis. The mean shift in slope resulting from considering inflation explicitly (deflator A, B, or C) was found to be a reduction of nearly 3% relative to the slope observed when inflation effects were ignored. (This magnitude of reduction is a function of the particular inflation environment, and may not be the same at another time.)

Since it would be desirable to know which alternative treatment is the best one to use, an attempt was made to rank the different deflators in terms of their relative performance on the measures reflected in the summary chart (Table 25). These rankings are shown in Table 27. The merit figures shown at the bottom of the chart are unweighted average rankings. If the various measures are considered to be of essentially equal importance, then the merit figures suggest that the two closely tailored deflators, AVPR and FPGS, rank first and second, followed by the broadly-based GNP deflator, with the alternative of ignoring inflation being the least desirable by an appreciable margin. If selected measures are emphasized and others discounted in importance, FPGS or GNP deflators might be favored over AVPR deflators. The alternative of ignoring inflation is totally dominated, and thus would never be preferred to any of the other three options, regardless of weightings. (The only exception would be the degenerate situation of short term analyses where inflation is not a relevant factor, as when all procurements in a sequence are compressed into a time interval of less than a year.)

To summarize, the Avionics Procurement deflators appear to perform best on the avionics data analyzed, but only marginally better than

TABLE 27 — PERFORMANCE RANKINGS OF INFLATION TREATMENTS

	Deflator			
	FPGS	GNP	AVPR	None
SLOPE				
MIN	1	3	2	4
MAX	1	2.5	2.5	4
MEAN	2	3	1	4
STD DEV	1	2	3	4
COEFFICIENT OF DETERMINATION				
MIN*	3	1	2	4
MAX*	2.5	2.5	2.5	2.5
MEAN*	3	2	1	4
STD DEV	3	2	1	4
SIGNIFICANCE				
MIN	2.5	2.5	2.5	2.5
MAX	2	3	1	4
MEAN	3	2	1	4
STD DEV	2	3	1	4
STANDARD ERROR OF ESTIMATE				
MIN	2.5	2.5	2.5	2.5
MAX	1	3	2	4
MEAN	2	1	3	4
STD DEV	1	3	2	4
MERIT FIGURE	2.0	2.4	1.9	3.7

* Highest magnitude from Table 25 ranks first (otherwise lowest best).

Federal Purchases of Goods and Services deflators (which are more readily available to the industrial public). The differential between Federal Purchases of Goods and Services and Gross National Product deflators is also small; only the alternative of ignoring inflation entirely is clearly set off as distinctly less desirable.

Implicit Prior Experience

Issue 3: How are the forms of experience curves affected by implicit prior experience on closely related products? Because no explicit data on related prior experience were available for comparisons, this aspect of the present research was limited to examining the consistency between shift factor (C) values determined in the context of avionics procurements and those previously determined in the Stanford research. In the course of the present research, it became apparent that there were substantial inconsistencies, with shift factor values observed exceeding expected values by factors of as much as 1000. Since a slope break pattern is often associated with competitive interactions, it was conjectured that abnormally high C values might be an effect of strong competition. Consequently, data on the extent of competition surrounding each procurement sequence analyzed has been introduced into the discussion in this section, although not originally planned to be a part of this aspect of the present research.

Regressions performed on the logarithmic model

$$\ln Y_A = \ln B_0 + B_1 \ln (X_1 + C) \qquad (19)$$

showed that the data content of 16 of the 30 subfiles examined (53%,

not significantly different from the expected 50%) could be represented in a statistically better manner when the shift factor (C) was assigned some value greater than zero. The approximately optimal values for C for each of the subfiles for which C exceeds zero are shown in Table 28, together with brief explanatory comments regarding the competitive environment. (The C values determined are only approximately optimal, in the sense of providing the most linear fit of data points to the model, since the trial values of C were adjusted in predetermined fixed increments, rather than by an iterative technique which would result in identification of true optimum values.)

For 10 of the 16 subfiles for which the regression fit was improved by this transformation of coordinates, the approximately optimal C value was found to be 300 or less, consistent with earlier observations by the Stanford Research Institute. For these values of C of 300 or less, the Stanford Research Institute explanation of C as reflecting effective learning carryover in the form of an implicit prior experience quantity does seem reasonable. However, in the other 6 subfiles, the inferred near-optimal values for C ranged from 10,000 to 300,000 or greater (300,000 was the highest value examined). Each of these extreme values related to a subfile influenced by competition, as briefly noted in Table 28. In each instance, either continuing or threatened competition was a relevant factor which could have served as the impetus for a sudden and sharp break in the established pricing trend. Regression techniques can demonstrate only association, not causality; however, the clear association of unusually high C values only with continuing or

TABLE 28 — IMPROVING FIT BY COORDINATE TRANSFORMATION

Subfile	Approx. C	Comments
1	100	Competition for Original Buy Only
2	3	Competition for Original Buy Only
4	3	Competition for Original Buy Only
6	300	Competition for Original Buy Only
9	300,000	Continuing Competition (4 Sources)
10	10,000	Industry Composite (4 Sources)
16	3	Competition for Original Buy Only
18	100	Competition for Original Buy Only
19	300,000	Threatened Competition (4 Bidders)
20	10,000	Continuing Competition (2 Sources)
22	300,000	Industry Composite (2 Sources)
24*	30,000	Continuing Competition (5 Sources)
25	30	Continuing Competition (5 Sources)
27	100	Industry Composite (5 Sources)
29	100	Continuing Competition (5 Sources)
32	30	Industry Composite (5 Sources)

Approximate C values for "best-fit" curves of form

$$\ln Y_A = \ln B_0 + B_1 \ln (X_1 + C)$$

NOTE: Subfiles not listed were best described by traditional model.

* In spite of competition, contractor exhibited learning loss (i.e., inverted version of pattern shown in Figure 4).

threatened competitive situations suggests that this particular relationship warrants further study.

For 29 of the 30 subfiles examined, the patterns of behavior of the regression parameters with shifts in C value were consistent. For the 29 consistent subfiles, the observed values of R^2, Adjusted R^2, and F-ratio were maximum at the near-optimal C value, and incrementally less for either higher or lower C values. For the same 29 subfiles, the observed values of the Standard Error of Estimate and the overall regression relationship significance were minimum at the near-optimal C value, and incrementally greater for either higher or lower C values. Subfile 08 contained the only observed exception to these patterns, exhibiting a best fit for C = 0, but also possessing minor localized inconsistencies in the trends of these parameters for C values of 1000 and greater. These inconsistencies are attributed to the unique data pattern of this subfile, which does not reflect experience gains.

For all 25 subfiles reflecting realization of experience gains (i.e., regression slope exponent values negative), the value of the imputed first unit intercept and the absolute value of the slope exponent increased with increasing C values. For all 5 subfiles not reflecting experience gains (i.e., regression slope exponent values positive), the value of the imputed first unit intercept decreased and the value of the slope exponent increased with increasing C values. Representative observed regression parameter values for the near-optimal C value, and for the next lower and higher C values examined, are presented in Appendix F for the 16 subfiles for which C exceeded zero.

In summary, this aspect of the present research suggests that effective retained experience, or implicit prior experience, may in fact be reflected in shift factors with values of up to perhaps 300 units. However, for substantially higher C values, such as 10,000 and greater, another explanation is needed. In this range, it appears that competitive pressures greatly distort price trend profiles. This effect is predicted by experience curve theory. Under that theory, a gradual price decline (relative to cost decline) invites market entry by competitors, and that entry in turn provides strong motivation for producers to force their own costs down more rapidly, thus permitting them to be price competitive.

Identification and further study of the factors influencing this sequence of events are important. Further pursuit of the coordinate transformation technique examined here does not seem worthwhile, though. This approach does not consider such experience factors as investment, specialization, or scale, and consequently results only in a statistically better model of historical price-quantity relationships, with little if any theoretical or intuitive appeal for its use in planning or predicting future activities. Attention should be devoted instead to developing models which will improve predictive power through incorporation of controllable production-related parameters which reflect, implicitly if not explicitly, the experience factors of investment, specialization, and scale, as well as the underlying learning phenomenon. Secondarily, more attention should be given to ways of recognizing trend patterns which can best be represented by piece-wise log-linear segments, particularly useful

for short-term projections or forecasts in the absence of critical external influences. Both of these ideas are developed further hereafter.

Production Parameters

Issue 4: How are the forms of experience curves related to production lot sizes, product delivery rates, delivery lead times, and the durations of breaks between production runs? Using stepwise multivariate regression techniques on the additive logarithmic model

$$\ln Y_A = \ln B_0 + B_1 \ln X_1 + B_2 \ln X_2 + B_3 \ln X_3 + B_4 \ln X_4 + B_5 \ln X_5 + B_6 \ln X_6 \quad (21)$$

the effects of each of the five postulated production parameters were found to be beneficial in from five to eight of the twelve production sequences for which adequate data were available to support the analyses. (The stepwise results of the regressions are provided for reference in Appendix G.) All twelve production sequence subfiles benefited from the introduction of at least one production parameter. In no case did a variable drop out of the regressions once introduced, and in no case did the sign of a coefficient change as additional variables were introduced.

As shown in Table 29, Cumulative Quantity (X_1) had the greatest explanatory power in every production sequence (as anticipated), entering every regression first. Of the five modulating parameters, Production Break Duration (X_4) most often entered the regressions second, followed closely by Delivery Lead Time (X_5) and Maximum

TABLE 29 — PRODUCTION PARAMETER ENTRY ORDER

Subfile	Variable X_1	X_2	X_3	X_4	X_5	X_6
01	1		3		2	
02	1	3	2			
03	1		3		2	4
04	1		3	2		
05*	1	5		3	2	4
06	1	Limited Data - No Improvement Possible				
11	1	6	5	3	2	4
12*	1	4	3	2		
13*	1	4		2	5	3
14	1	Limited Data - No Improvement Possible				
15	1		2			
16	1			2		
17	1		2		3	
18	1			2		3
MERIT FIGURE	1.00	4.40	2.88	2.29	2.67	3.60
# OF ENTRIES	14	5	8	7	6	5

* Learning slope greater than 100%.

X_1 = Cumulative Quantity X_4 = Production Break Duration

X_2 = Quantity Bought X_5 = Delivery Lead Time

X_3 = Maximum Delivery Rate X_6 = Average Delivery Rate

Delivery Rate (X_3). If frequency of regression entry, rather than average entry rank (the merit figure in Table 29), is used to determine relative importance, the sequence of these three parameters becomes X_3, X_4, and X_5. Relatively less important, but still contributing to increased explanatory power and reduced estimating error in five procurement sequences apiece, were Average Delivery Rate (X_6) and Quantity Bought (X_2).

The greatest observed magnitude of any production parameter coefficient was 0.06825, well below the expected 0.10000 maximum. The signs of the coefficients were not, however, found to be consistent with prior expectations. As shown in Table 30, only the sign of the Average Delivery Rate (X_6) coefficient was as expected (i.e., negative) more than half the time. Even the observed 80% agreement with expectation in this case may not be significant, since due to the small sample sizes, no meaningful statistical tests can be applied here. Recalling Figure 5 (page 101), the implications of inconsistent signs for parameters X_2, X_3, X_5, and X_6 can be rationalized in terms of the effective region of each theorized U-shaped curve. When the sign differs from that expected, the inference can be that the characteristics of the particular production sequence were such as to cause the effective region to be the opposite of that initially postulated (see Table 8). Data collected for the present research did not permit positioning firms on the price-parameter graphs of Figure 5. Future research could be directed at establishing these positions, and thus supporting or refuting the present inferred explanation of the meaning of signs opposite to those postulated.

TABLE 30 — PRODUCTION PARAMETER REGRESSION COEFFICIENTS

Subfile	Coefficient B_2	B_3	B_4	B_5	B_6
01		-.00352		-.01012	
02	+.00055	-.00137			
03		+.00911		+.00942	-.00687
04	-	+.00812	-.02536		
05*	-.01270		+.00646	-.05649	+.01390
06	Limited Data - No Improvement Possible				
11	-.00564	+.02028	-.00245	+.02302	-.01394
12*	+.01933	-.04378	-.03414		
13*	+.04179		-.04487	+.05441	-.06606
14	Limited Data - No Improvement Possible				
15		+.06825			
16			+.00104		
17		-.00782		-.00518	
18			-.01033		-.00298
EXPECTED SIGNS	-	+	+	-	-
% EXPECTED SIGNS	40	50	29	50	80

* Learning slope greater than 100%.

NOTE: Greatest observed coefficient magnitude = .06825.

Explanation of the unexpected preponderance of negative signs associated with the Production Break Duration (X_4) coefficient is not so straightforward. Competitive pressures cannot be credited, since continuing or threatened competition was not a factor after the first procurement in any of these procurement sequences. Conceivably, continuing production of similar products during these apparent production breaks could have sustained the beneficial experience trends. Alternatively, contractors may in some instances have used the break periods constructively to introduce process improvements or to make other managerial changes which would reduce costs more than enough to offset learning losses. Unfortunately, the data available are insufficient to assess the validity of either of these hypotheses. Future research in this area is particularly warranted, in view of the frequency with which this parameter entered regression equations as the most important modulating factor.

For all twelve procurement sequence subfiles for which available data permitted assessment of potential improvements in the explained variance and in the standard error of estimate, the introduction of one or more production parameters proved beneficial. As summarized in Table 31, the greatest percentage improvements were realized in terms of reductions in the standard error of estimate. (The only exception to this pattern was noted in subfile 13, where an unusually poor initial fit permitted exceptionally large increases in R^2 and Adjusted R^2 values.) For nine of the twelve subfiles, the introduction of production parameters caused the imputed learning slope to become slightly steeper. However, the difference between the means of the

TABLE 31 — PRODUCTION PARAMETER EFFECTS

Subfile	Percentage Changes R^2	Adjusted R^2	SEE	Learning Slope
01	.415	.359	-13.671	-.097
02	.012	.007	-9.489	-.064
03	1.182	.648	-5.938	.518
04	.432	.326	-10.313	.176
05*	7.448	8.408	-69.935	.562
06	Limited Data - No Improvements Possible			
11	.151	.086	-13.671	.400
12*	20.396	16.289	-26.843	2.336
13*	117.855	94.515	-16.740	1.049
14	Limited Data - No Improvements Possible			
15	.531	.601	-40.406	-2.297
16	.025	.016	-4.545	-.169
17	.566	.487	-14.200	-.539
18	1.437	1.011	-6.813	-.349
MEAN**	.528	.393	-13.227	-.269

* Learning slope greater than 100%.

** Excluding subfiles 05, 12, and 13.

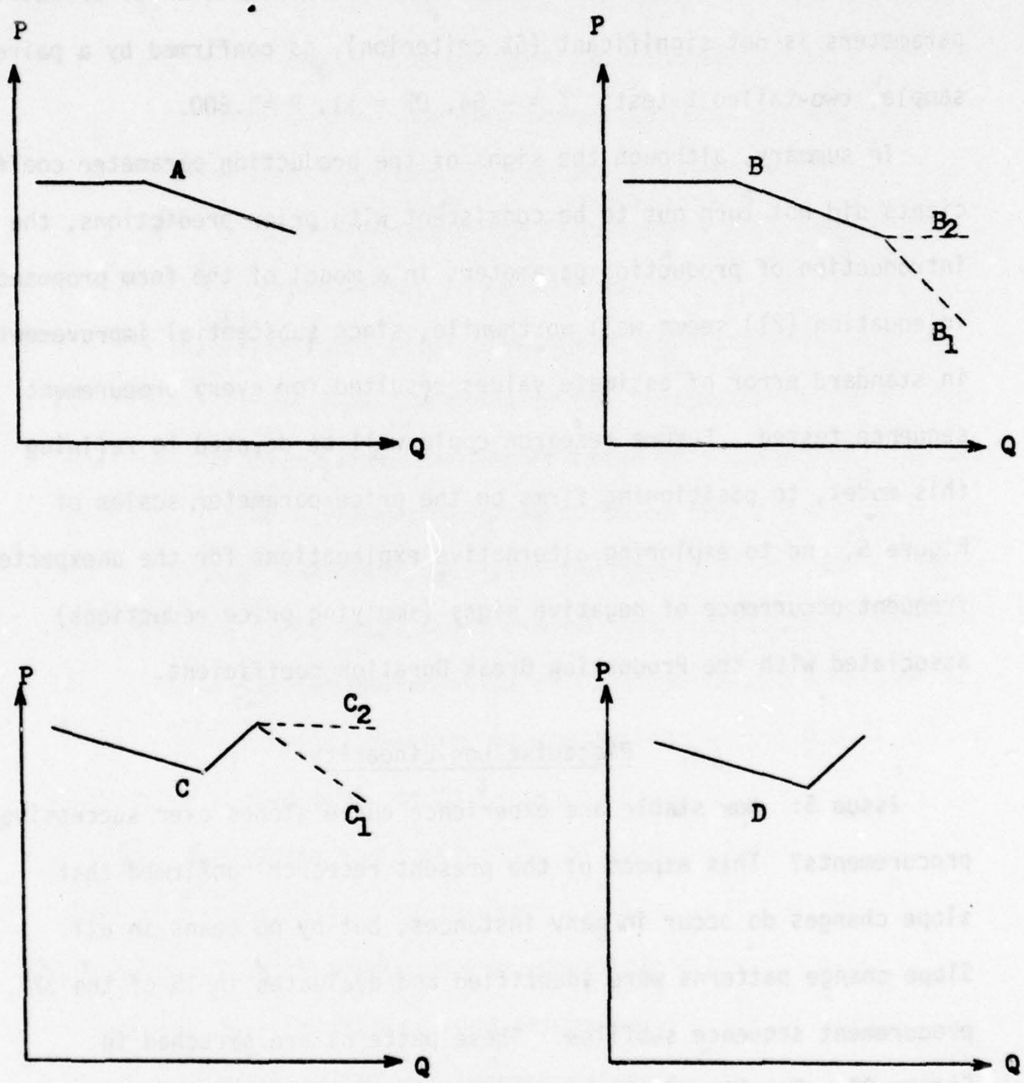
imputed learning slopes before and after the introduction of production parameters is not significant (5% criterion), as confirmed by a paired-sample, two-tailed t-test: T = -.54, DF = 11, P = .600.

In summary, although the signs of the production parameter coefficients did not turn out to be consistent with prior predictions, the introduction of production parameters in a model of the form proposed in equation (21) seems well worthwhile, since substantial improvements in standard error of estimate values resulted for every procurement sequence tested. Future research could well be devoted to refining this model, to positioning firms on the price-parameter scales of Figure 5, and to exploring alternative explanations for the unexpectedly frequent occurrence of negative signs (implying price reductions) associated with the Production Break Duration coefficient.

Piecewise Log-Linearity

Issue 5: How stable are experience curve slopes over successive procurements? This aspect of the present research confirmed that slope changes do occur in many instances, but by no means in all. Slope change patterns were identified and evaluated in 15 of the 32 procurement sequence subfiles. These patterns are sketched in Figure 23. Results of the supporting regression analyses, compared later in this section, are reported for reference in Appendix H.

The commonest pattern (A in Figure 23), observed in six subfiles, involved only one break point: an initial nearly level or gradually declining slope (values from .86339 to 1.00823), followed by a relatively steeper decline (from .74414 to .88279). This pattern is



PATTERN	SUBFILES
A	01, 04, 09, 10, 20, 22
B_1	18
B_2	19
C_1	03, 13
C_2	23, 27, 32
D	12, 31

FIGURE 23 — SLOPE CHANGE PATTERNS

consistent with the experience curve effect implication that price should initially be set near costs, then decreased with costs to inhibit market entry by competitors. The inference is that prices were not reduced markedly until either an adequate profit margin was realized, or the threat of competition forced a price slope break. In two instances (subfiles 01 and 04), this pattern developed in the absence of competition, in two (09 and 20) it developed under competitive pressures, and in two (10 and 22) it reflects cross-contractor item-industry composite behavior. A variant (B) of this basic pattern, exhibiting a second break point, was demonstrated by two contractors. In one instance (B_1; subfile 18), the second break was followed by a still steeper slope, even though competition was not a factor. In the other (B_2; subfile 19), the second break was followed by a nearly level slope, again in the absence of competitive pressures; this was the only observed instance of the "reversed-S" pattern suggested by Asher.

The second commonest pattern (C), observed in five subfiles, involved two break points: an initially declining slope (values from .84033 to .97754), followed by a rising slope (from 1.02459 to 1.27138), followed finally by another declining slope (from .86831 to .95396). In two instances (C_1; subfiles 03 and 13), both in the absence of competition, the final slope decline was steeper than the initial decline. In the other three subfiles (C_2; 23, 27, and 32), the first in the absence of competition but the other two reflecting cross-contractor item-industry composite behavior, the final slope decline was more gradual than the initial decline. The observed variant (D)

of this pattern, demonstrated by two contractors, omitted the second break point: the period of rising prices ended with termination of production. For one contractor (subfile 12), performing without competition, the price rise may have been associated with end-of-run cost increases, as described in Chapter II. For the other (subfile 31), apparent inability to reduce price forced early withdrawal from a strongly competitive market (five sources).

Although the first slope break point (all patterns) for individual contractors ranged from the third to the thirteenth buy, the median value was the fourth buy; the second break point, when it occurred (patterns B and C), ranged from the fifth to the fifteenth buy, with a median value of the tenth buy. For the item-industry composite patterns, the first break point ranged from the fourth to the ninth buy, with an implied median value of 7.5; the second break point (observed only twice) occurred at the twelfth or fourteenth buy, implying a median value of 13.

To investigate the feasibility of using adjacent slope values, and more particularly the standard deviation of those values, as an indicator of which production sequences could benefit from piecewise treatment, adjacent slopes were determined for the price-quantity relationships of all 32 procurement sequence subfiles. (These values are summarized in detail in Appendix H.) Thirty subfiles contained sufficient data to establish adjacent slope standard deviation values; the value 0.065 was identified as distinguishing the least variable one-third of these subfiles from the higher variability two-thirds. Although 13 of the subfiles analyzed for piecewise log-linearity

belonged to the high variability sample, a chi-square test value of 2.7 (1 DF) confirmed that the relation between adjacent slope variability and selection for piecewise analysis was not significant (5% criterion). On the other hand, a t-test comparison of the subfile regression slopes and their counterpart mean adjacent slopes supported acceptance of the null hypothesis that the different measurement approaches reflect the same underlying phenomenon: T = -1.15, DF = 27, P = .260. Thus, although the mean value of the easily computed adjacent slopes is a good estimator of the regression slope, the variability of the adjacent slope values is not a good indicator of patterns amenable to piecewise analysis.

The key regression characteristics (i.e., coefficient of determination, standard error of estimate, significance, and slope) were determined for each segment of each subfile identified for analysis; these values are reported in Appendix H. The results of chi-square test comparisons of the relative frequencies of increase and decrease in the magnitudes of the key characteristics (compared pairwise among the overall regression, first segment regression, and last segment regression) are summarized in Table 32. As expected, increases in the coefficient of determination values for first segment regressions relative to overall regressions were found to be highly significant (1% criterion), as were decreases in the standard error of estimate values for both the first and last segment regressions relative to overall regressions. Test results also indicated that overall regression significance magnitudes increased significantly (i.e., the regressions tended to be less significant) for first segment

TABLE 32 — PIECEWISE LOG-LINEARITY CHI-SQUARE COMPARISONS

Segments	Frequency Increase	Frequency Decrease	Chi-Square
COEFFICIENT OF DETERMINATION			
First: Overall	13	2	8.067
Last: Overall	11	4	3.267
Last: First	6	9	0.600
STANDARD ERROR OF ESTIMATE			
First: Overall	2	13	8.067
Last: Overall	0	15	15.000
Last: First	4	11	3.267
SIGNIFICANCE			
First: Overall	12	3	5.400
Last: Overall	8.5	6.5	0.267
Last: First	6	9	0.600
EXPERIENCE SLOPE			
First: Overall	8	7	0.067
Last: Overall	5	10	1.667
Last: First	6	9	0.600

H_0: $f_I = f_D$ vs. H_A: $f_I \neq f_D$

NOTE: Critical value of Chi-Square (5% level, 1 DF) = 3.841

regressions relative to overall regressions; this unexpected result is attributed to the small numbers of data points typically analyzed in the first segment regressions. The only other unexpected result was that the increase in coefficient of determination values for last segment regressions relative to overall regressions was significant only at a 10% criterion, not at the 5% level; since standard error of estimate increases were highly significant, this is not considered to be a problem. As anticipated, none of the other comparisons made were conclusive, although last segment regression standard error of estimate values clearly tended to be lower than counterpart first segment values (significant only at a 10% level).

It was noted with interest that the mean last segment regression slope for the nine contractors demonstrating experience gains (i.e., slope values less than 100%) for that segment was 87.5%, considerably steeper than the 93.8% mean value of the overall regression slopes of these same nine contractors. This pronounced differential suggests that overall regression slopes may often be unduly conservative (i.e., too flat, thus overestimating prices), but also provides warning that projections based on piecewise log-linear regressions may be seriously understated if some unrecognized factors disrupt the segment trend.

In summary, clear slope change patterns were identified in 47% of the procurement sequence subfiles. The commonly held view in the military procurement environment that an experience slope for a particular product and firm remains constant once established is thus refuted.

Slope Variability

Issue 6: How consistent are experience curve slopes within and across firms? Experience slope data developed for the analysis of Issue 2 and reported in Table A6 (Appendix E) was examined for consistency and found to be highly variable. The extent of this variability across items within firms is evident in Table 33. None of the six individual firms considered exhibited a slope standard deviation value as low as the "desirable" maximum value of .01276, even when subfiles with slopes greater than 100% were excluded as non-representative. On the other hand, the reduced variability associated with composite measures was evidenced by the desirably narrow range of cross-contractor regression slopes for four different products.

The similar extent of this variability within items across firms is shown in Table 34. For only one of four products considered (item 7) was the slope standard deviation value as low as the desirable maximum value of .01276, and then only when the performance of a firm with slope in excess of 100% was excluded. It was also noted that for only one product (item 20) was the mean of individual firm slopes within 2.5% of the overall composite regression slope for that product.

Communication, Navigation, and Composite (i.e., all subfiles) cross-contractor aggregations were examined, with results as shown in Table 35. Again, all slope standard deviation values for these aggregations were considerably larger than the desirable .01276, regardless of whether slopes in excess of 100% were included, excluded, or truncated to 100%. The differences between the aggregations

TABLE 33 — SLOPE VARIABILITY WITHIN FIRMS

Firm	# of Items	Slope Measures Max	Min	Mean	Std Dev
ALL SUBFILES CONSIDERED					
5	2	1.09644	.87149	.98397	.15906
6	6	1.04564	.85446	.92819	.06913
8	2	.94469	.91821	.93145	.01872
10	6	.95525	.83080	.89314	.04705
11	5	1.05445	.82657	.92568	.10280
13	2	.90476	.84458	.87467	.04255
ALL*	4	.93963	.91494	.93114	.01144
SUBFILES WITH SLOPE > 100% EXCLUDED					
5	1	.87149	.87149	.87149	-
6	5	.96238	.85446	.90469	.04284
8	2	.94469	.91821	.93145	.01872
10	6	.95525	.83080	.89314	.04705
11	3	.88216	.82657	.85269	.02795
13	2	.90476	.84458	.87467	.04255
ALL*	4	.93963	.91494	.93114	.01144

* ALL refers to cross-contractor composites per Table 7.

TABLE 34 – SLOPE VARIABILITY FOR ITEMS ACROSS FIRMS

	Item 7	Item 17	Item 19	Item 20
ALL SUBFILES CONSIDERED				
MAX	1.03884	.91821	1.09644	1.08221
MIN	.96238	.89819	.84458	.87149
MEAN	.99014	.90820	.95404	.94321
STD DEV	.04231	.01416	.12912	.09447
# OF FIRMS	3	2	3	4
ALL*	.93963	.93877	.91494	.93123
SUBFILES WITH SLOPE > 100% EXCLUDED				
MAX	.96920	.91821	.92111	.91437
MIN	.96238	.89819	.84458	.87149
MEAN	.96579	.90820	.88285	.89687
STD DEV	.00482	.01416	.05411	.02250
# OF FIRMS	2	2	2	3
ALL*	.93963	.93877	.91494	.93123

* ALL refers to the overall regression slope for cross-contractor composites, per Table 7.

TABLE 35 — COMPOSITE SLOPE VARIABILITY ACROSS FIRMS

	Items: Communication	Items: Navigation	Composite
ALL SUBFILES CONSIDERED			
MAX	1.05445	1.09644	1.09644
MIN	.82657	.83080	.82657
MEAN	.94273	.92443	.93162
STD DEV	.08806	.07226	.07778
# OF SUBFILES	11	17	28
SUBFILES WITH SLOPE > 100% EXCLUDED			
MAX	.96920	.96047	.96920
MIN	.82657	.83080	.82657
MEAN	.88789	.90245	.89782
STD DEV	.05603	.03947	.04454
# OF SUBFILES	7	15	22
SLOPES > 100% TRUNCATED TO 100%			
MAX	1.00000	1.00000	1.00000
MIN	.82657	.83080	.82657
MEAN	.92866	.91392	.91971
STD DEV	.07129	.04912	.05802
# OF SUBFILES	11	17	28

MEAN SLOPE COMPARISONS, COMMUNICATION VS. NAVIGATION

	Mean	Std Dev
ALL SUBFILES CONSIDERED	.93358	.01294
SUBFILES WITH SLOPE > 100% EXCLUDED	.89517	.01030
SLOPES > 100% TRUNCATED TO 100%	.92129	.01042

Communication and Navigation were small. With slopes in excess of 100% excluded or truncated, the standard deviation of the mean slopes for these two aggregations was well below (i.e., .01030 and .01042, respectively) the desirable maximum value, and even including those extreme slopes, the standard deviation only slightly exceeded the desirable value (i.e., .01294 vs. .01276). Regardless of the treatment of extreme slopes, the mean of the Communication and Navigation aggregation mean slopes was within 0.3% of the corresponding Composite mean.

In summary, slopes are not highly consistent either within or across the firms examined, even though there is relatively little variability amongst sub-industry composite mean slope values. Based on the present research, the rank ordering by Harris et al. (1965) of alternative techniques for estimating an unknown slope (summarized on page 64) cannot be refuted, but neither can it be strongly supported. The findings here are not inconsistent with those of Waggoner (1971), reported in Table 4, when consideration is given to the fact that these findings are based on the use of FPGS deflators, whereas his ignored inflation. These findings strongly suggest the desirability of making multiple projections, using a range of potential slope values, when planning for new product introduction; to limit projections to a single estimated slope is to unwisely ignore the risks and uncertainties inherent in forecasting. Decision makers forced to contend with alternative projections will benefit from a better understanding of the assumptions and risks inherent in each alternative.

For future research, an alternative (and potentially more useful) approach to the analysis of slope variability might be to develop a product complexity factor, and then to examine the degree to which this factor contributes to experience slope differences amongst a contractor's products. Similarly, an overall experience level factor might be developed to facilitate cross-contractor comparisons. Thirdly, simulations could be used to determine the sensitivity of cost or price projections to errors in slope estimating. While it is clear that a small percentage error in slope will lead to increasingly large errors in cost or price projections with increasing cumulative quantities (Hartung, 1969, 1970), it would be useful to have nomographs or tables to depict the relationships.

Future Price Prediction

Issue 7: How accurately can future procurement pricing be predicted using experience curve theory? Four price prediction methods were compared:

A) Overall Regression, Traditional Model,

B) Overall Regression, Production Parameter Model,

C) Last Log-Linear Segment Regression, Traditional Model, and

D) Last Log-Linear Segment Regression, Production Parameter Model.

For the twelve avionics data subfiles analyzed, the predictive abilities of all four models tested were surprisingly good (i.e., deviation values were less than 5%). Results of these analyses are provided for reference in Appendix I, in terms of both dollar and percentage deviations

of predicted values from actual values. For the first, second, and third buys beyond the range of the model data, those results are summarized in terms of mean absolute deviation (MAD), average deviation (Bias), and Theil's U measures, in Tables 36 through 38.

For all dollar-based comparisons, model D appeared to perform best on all measures, followed by C, then B, and lastly by A. Indications of these measures for percentage-based comparisons were not quite so clear cut; only for second buy predictions did all measures appear to consistently support the dollar-based model preference order. For first and third buy predictions, the measures appeared to suggest that model A might be better than B, and C might be better than D (contrary to anticipated results).

To assess the statistical significance of these apparent patterns of model behavior, paired-sample, one-tailed t-tests were performed on the percentage-based results to determine if Bias values differed significantly under the application of alternative methods. The results of these t-tests are displayed in Tables 39 through 41, for first through third buy predictions, respectively. Using the predetermined significance criterion of 5%, models C and D were found to be significantly better in performance than model A under every comparison. Similarly, rounding significance values to the nearest percent, models C and D were found to be significantly better than model B under every comparison. However, model B performed significantly better than model A only under the second buy comparisons, and model D was never demonstrated to be significantly better than C.

TABLE 36 — COMPARISON OF 1ST BUY PREDICTIONS

Method	Methods Compared ($ Basis)/(% Basis) A B	A C	A B C D
		MAD	
A	470.80 2.150	634.78 3.995	733.40 3.300
B	346.82 2.058	-	523.08 3.207
C	-	153.86 .892	162.11 .596
D	-	-	148.41 .622
		BIAS	
A	459.75 2.095	634.78 3.995	733.40 3.300
B	328.33 1.787	-	520.61 2.873
C	-	152.12 .659	159.36 .223
D	-	-	145.90 .282
		THEIL'S U	
A	.02817 .02889	.03252 .04261	.03141 .03481
B	.01884 .03028	-	.02086 .03974
C	-	.00885 .01011	.00835 .00668
D	-	-	.00732 .00651

TABLE 37 – COMPARISON OF 2ND BUY PREDICTIONS

Method	Methods Compared ($ Basis)/(% Basis) A B	A C	A B C D
	MAD		
A	530.46 2.511	710.17 4.695	814.82 3.813
B	332.60 1.937	-	434.60 2.663
C	-	182.38 1.022	207.19 .802
D	-	-	140.47 .748
	BIAS		
A	506.08 2.381	710.17 4.695	814.82 3.813
B	291.15 1.641	-	433.76 2.550
C	-	180.28 .738	203.83 .348
D	-	-	131.19 .068
	THEIL'S U		
A	.03116 .03215	.03608 .05168	.03470 .04121
B	.01716 .02612	-	.01827 .03316
C	-	.01122 .01077	.01092 .00897
D	-	-	.00635 .00769

TABLE 38 — COMPARISON OF 3RD BUY PREDICTIONS

Method	Methods Compared ($ Basis)/(% Basis) A B	A C	A B C D
		MAD	
A	552.45 2.543	759.74 4.989	838.63 3.777
B	393.08 2.311	-	546.88 3.278
C	-	209.40 1.299	221.26 1.012
D	-	-	198.89 1.117
		BIAS	
A	505.32 2.289	759.74 4.989	838.63 3.777
B	309.96 1.588	-	543.82 2.866
C	-	202.76 .763	210.64 .154
D	-	-	180.03 -.060
		THEIL'S U	
A	.03210 .03226	.03792 .05461	.03575 .04118
B	.02151 .03125	-	.02362 .04023
C	-	.01222 .01499	.01133 .01075
D	-	-	.01012 .01200

TABLE 39 — T-TESTS ON 1ST BUY PREDICTIONS

(ABCD) Comparisons

	B	C	D
Model A			
T	.45	6.85**	7.50**
DF	4	4	4
P	.338	.001	.001
Model B			
T		2.09*	2.08*
DF	-	4	4
P		.053	.054
Model C			
T			-.75
DF	-	-	4
P			.249

(AB) and (AC) Comparisons

	B	C
Model A		
T	.61	7.25**
DF	8	7
P	.280	.000

T = Computed T Value

DF = Degrees of Freedom

P = One-Tailed Probability

NOTE: Tests compared percentage-based Biases.

* Significant at 5% Criterion.

** Significant at 1% Criterion.

TABLE 40 — T-TESTS ON 2ND BUY PREDICTIONS

	(ABCD) Comparisons		
	B	C	D
Model A			
T	2.98*	5.57**	5.19**
DF	4	4	4
P	.021	.003	.004
Model B			
T		2.36*	2.33*
DF	-	4	4
P		.039	.040
Model C			
T			1.31
DF	-	-	4
P			.130

	(AB) and (AC) Comparisons	
Model A		
T	2.30*	5.38**
DF	8	7
P	.026	.001

T = Computed T Value

DF = Degrees of Freedom

P = One-Tailed Probability

NOTE: Tests compared percentage-based Biases.

* Significant at 5% Criterion.

** Significant at 1% Criterion.

TABLE 41 — T-TESTS ON 3RD BUY PREDICTIONS

(ABCD) Comparisons

	B	C	D
Model A			
T	1.28	5.29**	6.53**
DF	4	4	4
P	.136	.003	.002
Model B			
T		2.21*	2.13*
DF	-	4	4
P		.046	.050
Model C			
T			-.95
DF	-	-	4
P			.199

(AB) and (AC) Comparisons

	B	C
Model A		
T	1.73	5.71**
DF	8	7
P	.061	.001

T = Computed T Value

DF = Degrees of Freedom

P = One-Tailed Probability

NOTE: Tests compared percentage-based Biases.

* Significant at 5% Criterion.

** Significant at 1% Criterion.

The implications of these tests are that the predictive ability of price experience curves can be significantly enhanced (relative to the traditional model A) by breaking them into log-linear segments (model C). While the introduction of production parameters in conjunction with the traditional form (model B) appeared to improve dollar-based performance measures, the statistical tests indicate that the improvement is not always significant. Since less data are needed for application of model C than of B, the former should generally be preferred. Similarly, introduction of production parameters in conjunction with log-linear segments (model D) did not provide statistically significant improvement. In view of their apparently good performance as indicated by dollar measures, however, more research into production parameter models should be encouraged.

CHAPTER VII — CONCLUSIONS AND RECOMMENDATIONS

This closing chapter presents overall conclusions and recommendations based on the present research. Future academic research opportunities are identified and outlined. Finally, recommendations are proffered for desirable future actions by both buyers and sellers in the defense market place.

Conclusions

The first issue asked "How do experience curves differ from traditional learning curves in the Government procurement environment?" Analysis of the performance of defense avionics contractors indicates that price usually follows costs in the Government market place as it does in consumer and industrial markets, although with experience curve slopes typically of 85% to 95%, rather than the 70% to 80% observed in those latter markets. This relatively gradual rate of experience realization appears to be due both to the extent of Government interventions and controls, and to the concern of Government decision-makers for maintaining flexibility at the expense of productivity. For individual contractors, moderately significant predictive relationships were found to relate price experience slope to learning slopes for direct labor costs, purchased material costs, and total manufacturing costs. However, no significant relationships were identified at the sub-industry composite level, suggesting that price predictions based

solely on industry average cost slopes are predestined to be inaccurate. In most instances, the best statistical fits of data to theory resulted when cumulative average experience curves were fitted to price data.

The second issue asked "How are the forms of experience curves affected by alternative techniques for compensating for the effects of inflation?" The performance of the three alternative deflators analyzed was generally quite similar, in terms of visible effects on the shape of graphically displayed data. Ignoring inflation was found to result in relatively flat slopes with pronounced perturbations; Gross National Product (GNP), Federal Purchases of Goods and Services (FPGS), and Avionics Procurement (AVPR) deflators yielded increasingly steeper slopes for the same underlying data, with fewer perturbations. This ordering of the deflators in terms of slope steepness was found to be statistically significant, with the least distinction between the two closely tailored deflators (FPGS and AVPR). Based on the relative importance attached to various performance measures (e.g., slope steepness, explanation of variance), any one of the three deflators may be slightly preferred relative to the others for a particular analysis; only the alternative of ignoring inflation is consistently dominated.

The third issue asked "How are the forms of experience curves affected by implicit prior experience on closely related products?" Introduction into the traditional learning model of a positive shift factor, commonly thought to represent an implicit prior experience quantity, resulted in improved statistical fits in half of the procurement sequences investigated. In ten instances, the prior

experience interpretation seemed reasonable. However, in six instances shift factors of 10,000 or more suggested the need for an alternative interpretation. In each of these six instances, continuing or threatened competition was a relevant factor which could have served as the impetus for the observed sudden and sharp break in the established pricing trend. Establishment of a causal relationship was beyond the scope of the present research. Since the coordinate transformation approach does not consider such experience factors as investment, specialization, or scale, it does not add to the explanatory or predictive power of experience theory (even though statistically better fits can result from shift factor introduction). Further pursuit of this coordinate transformation technique does not seem worthwhile; other models and additional variables need to be considered if prior experience is to be explicitly recognized.

The fourth issue asked "How are the forms of experience curves related to production lot sizes, product delivery rates, delivery lead times, and the durations of breaks between production runs?" Five production parameters were proposed as implicitly recognizing the experience factors of investment, specialization, and scale. In multivariate regressions, the effects of each of these five postulated production parameters were found to be beneficial in increasing explained variance and reducing the standard error of estimate in from five to eight different procurement sequences (of the twelve analyzed). In no case did a variable drop out of the regressions once introduced, and in no case did the sign of a coefficient change as additional variables were introduced. Cumulative Quantity (the traditional

independent variable in learning or experience theory) was invariably the most significant contributor to the explanation of price shifts. Production Break Duration, Delivery Lead Time, and Maximum Delivery Rate were found to be the most significant modulating parameters, with no clearcut order of preference amongst them. Average Delivery Rate and Quantity Bought were also important. A surprising finding was that the apparent effect of extended Production Break Durations was usually to reduce, rather than increase, price. Competitive pressures cannot be credited, since continuing or threatened competition was not a factor in any of these instances. Two possible explanations would be that continuing production of similar products during these production breaks could have sustained beneficial experience trends, or that contractors may have used the breaks constructively to implement other cost reductions.

The fifth issue asked "How stable are experience curve slopes over successive procurements?" Slope change patterns were identified and evaluated in 15 of the 32 procurement sequences investigated. The commonest pattern (6 instances) involved only one break point, with an initial nearly level or gradually declining slope followed by a relatively steeper decline; this pattern is consistent with the experience curve effect implication that price should initially be set near costs, then decreased with costs (once a satisfactory profit margin is realized) to inhibit market entry by competitors. The second commonest pattern (5 instances) involved two break points, with an initially declining slope followed by a rising slope, followed finally by another decline. This pattern suggests that contractors encountered problems

leading to higher than planned costs, overcame them, and continued to realize experience gains. An alternative view would explain this as a pattern of buy-in (price below cost) until the market is assured, increase price to a profitable level, then reduce price with costs to reduce the risk of competitive entries. Breaking each of these 15 procurement sequences into two or three log-linear segments resulted in statistically significant improvements in the fit of the models to the data; the most notable improvement was in the reduction of standard error of estimate magnitudes. The mean last log-linear segment regression slope for the nine procurement sequences demonstrating experience gains for that segment was 87.5%; this was substantially steeper than the 93.8% mean value of the overall regression slopes for these same nine sequences. This pronounced differential suggests that overall regression slopes may often be unduly conservative (i.e., too flat, thus overestimating prices), but also provides warning that projections based on piecewise log-linear regressions may be seriously understated if some unrecognized factors disrupt the segment trend.

The sixth issue asked "How consistent are experience curve slopes within and across firms?" Regression slopes were found to be highly variable, both within and across firms. These findings strongly suggest the desirability of making multiple projections, using a range of potential slope values, when planning for new product introduction or for resumption of production following a major disruption (e.g., extended break, facility relocation, product or process redesign). Since slopes were not found to be consistent even within firms, let alone across firms, arbitrary reliance on any one slope

value for forecasting purposes, whether believed representative of the product line, the firm, or the industry, should be avoided. Development of forecasting models which expressly recognize relative product complexity and a contractor's overall experience level should offer opportunities for improvements relative to the current traditional models, reducing dependence on learning slope identification and prediction.

The seventh and final issue asked "How accurately can future procurement pricing be predicted using experience curve theory?" For the twelve avionics data subfiles analyzed, the predictive abilities of all four methods tested were surprisingly good (i.e., deviation values were less than 5%). The results achieved with the last log-linear segment methods were found to be more statistically significant than those achieved with overall regression methods, testing on percentage-based performance comparisons. The production parameter overall regression method was significantly better than the traditional overall regression method only in projecting prices for the second buy beyond the range of the model data; the last log-linear segment production parameter regression model was never demonstrated to be significantly better than the last log-linear segment traditional regression model, even though dollar-based measures (not amenable to statistical tests) appeared to favor it as the best of the four methods. Significance tests not withstanding, in view of the seemingly good performance of the production parameter models in reducing standard error of estimate values, and as indicated by dollar measures, these models warrant further investigation and refinement.

In the course of the present research, several ideas were identified which are deserving of further research beyond the scope of this effort. Also, implications of the present research for future Government avionics procurements need to be emphasized. Recommendations for future academic research and for future procurement actions (by both buyers and sellers) thus constitute the remainder of this chapter.

Research Recommendations

Experience curves are still a relatively new concept, and there remain several opportunities for constructive research. Four opportunity areas were recognized as particularly promising during the course of the present research, but were set aside as being beyond its scope. These areas are identified as Forecast Sensitivity Analyses, New Explanatory Factors, Production Parameter Model Refinements, and Slope Break Cause Investigations. The key elements of each research opportunity area will be discussed in the following paragraphs.

Forecast sensitivity analyses could be performed to determine quantitative relationships between price projections and various parameters influencing those projections. For instance, what are the effects of slope identification errors? Similarly, what are the effects of imputed first unit intercept magnitude errors? What are the effects on price projections of using alternative deflators in compensating for inflation? Through the use of computer simulation routines, it should be possible to explore these and similar questions. Based on these explorations, it should then be possible to develop both mathematical models and graphic guides to be used in clarifying

the range of potential inaccuracies associates with a forecast. The added insights into forecast uncertainties would in turn help decision makers in assessing the risks and probable outcomes of alternative strategies. Present single slope projection techniques are not fully adequate, and even the occasional consideration of confidence interval limits about such projections is only a preliminary step towards the desired quantification of uncertainty.

New explanatory factors can probably be developed to help determine the rate of experience realization which can reasonably be expected for new products, or for continued production of established products following a major disruption (e.g., substantial design change or extended production break). Three interesting concepts for such factors include: 1) A Commonality or Uniqueness factor, relating to process design; 2) A Complexity factor, relating to product design; and 3) An Experience Potential factor, relating to corporate policies. The intent of a Commonality/Uniqueness factor would be to capture relevant effective process experience by reflecting the degree of similarity between a product's manufacturing processes and those for other products recently or currently in production. The intent of a Complexity factor would be to reflect the potential for productivity increases inherent in the product's design, under the assumption that greater opportunities for improvement are associated with more complex designs. The intent of an Experience Potential factor would be to reflect the degree to which a firm's strategy and policies contribute to realization of experience gains. This last factor might be scaled in accordance with such considerations as a firm's willingness and ability to make capital

investments in facility and process improvements, or its attitudes towards standardization versus flexibility. Functional models to be examined in this opportunity area should include

Product Price Experience Slope = f (Firm Average Price Experience Slope, Commonality/Uniqueness Factor, Complexity Factor, Production Parameters)

and alternatively (for new firms with little or no basis for their own firm average slope or Commonality/Uniqueness and Complexity factors)

Product Price Experience Slope = f (Industry Average Price Experience Slope, Experience Potential Factor, Production Parameters).

While considerable research would be required to define and scale these factors, probably involving questionnaire and interview methods and multivariate data analysis techniques, the results could be particularly worthwhile.

As indicated earlier, the production parameter model examined in the present research appears to show considerable promise, but it could doubtless be refined and improved. Other model forms, rather than the simple multiplicative power form, might be tested. Other forms of analysis, such as weighted or non-linear regressions, could be tried. Other parameters could be introduced, such as production rates (rather than delivery rates), or Commonality/Uniqueness and Complexity factors, as outlined above. Additional data could be collected in future research to permit scaling the position of each firm with respect to each production parameter, thus enabling the investigator to determine

based on data, rather than on hypothesis, the expected signs of the parameter coefficients. Anecdotal evidence should be collected and interpreted with regard to activities during production breaks, in an effort to explain the apparent tendency of price to decrease with increased production break duration. Some aspects of this opportunity area, such as alternative models and analytical techniques, could be pursued without gathering additional data.

Slope break cause investigations are also strongly indicated as worthy of further research, based on the present work. It has been proposed that price experience slope breaks reflect implicit prior experience, but the present research suggested that strong competitive interactions are an alternative cause. Technological advances permitting major process improvements, and hence cost and price reductions, are another possible explanation. It should be beneficial to select for further analysis a few firms which have exhibited slope breaks, and to seek to positively identify the events or activities contributing to those breaks. Other specific avenues of inquiry could also be pursued. For instance, if prior experience quantities were explicitly known, it might be possible to relate these to some implicit measure of that experience. Simulation methods might be applicable here. Alternatively, using data on lengthy production sequences, early buys could be set aside for treatment as prior experience, and the later buys analyzed as if those early buys actually represented prior experience, rather than prior continuing production. An improved understanding of slope break causes and patterns should facilitate earlier recognition of the occurrence of such breaks, in turn permitting the

prompt introduction of log-linear segments for better forecasts. Such an improved understanding might also enable analysts to anticipate and predict when such breaks are likely to occur.

Procurement Recommendations

This concluding section provides recommendations for both buyers and sellers in the defense market place. These recommendations are based mainly on the two major findings in the present research: 1) Experience curve theory is applicable to Government procurements, but 2) The rate of realization of experience is less than in consumer and industrial product markets. (Other findings of the present research concern the mechanics of application and interpretation of experience curves, particularly with regard to slope and price projections useful in life cycle cost analyses. Implications of these other findings are not expanded here.) Recommendations deriving from the first major finding are presented from the perspective of interpretation of general business strategy implications. Recommendations deriving from the second major finding are presented from the perspective of implications for buyer-seller interactions. Each of these perspectives will be further introduced before proceeding with the actual recommendations.

The present research has confirmed that price usually follows cost (i.e., total manufacturing cost) even in the unique environment of the defense market place. Consequently, it is appropriate to interpret the general business strategy implications of the experience curve effect in the context of military procurement. Recommendations relating to business strategy will be presented grouped around five core ideas:

Price and Competitive Interaction, Technology and Market Share, Product Growth Rate, New Product Introduction, and Procurement Planning and Negotiations.

Consideration of buyer-seller interactions offers a more useful perspective for the remaining recommendations, based on the finding that experience realization is more gradual in the defense market place than in consumer and industrial markets. This fact may be attributed in part to the extent of intervention by the Government customer in decisions which, in other markets, would be within the purview of the producer. Additionally, it is due in part to unique aspects of the defense market place which affect producer risks, reduce incentives, and inhibit productivity gains. These explanations provide the framework for further recommendations. Emphasizing buyer-seller interactions, these complementary recommendations will be structured around four core ideas: Government Intervention, Producer Risks, Producer Incentives, and Productivity Inhibitors.

With a focus on business strategy, consider first the idea of price and competitive interaction. Experience theory holds that market instability develops when price does not follow cost. In openly competitive markets, instability leads to a price break, followed by a shakeout of marginal producers until price again stabilizes near cost, resulting in lower prices for customers and reduced profit margins for the surviving firms. In the military market place, similar patterns occur when there is open competition, but open competition is rarely maintained. Usually, once a firm wins an initial competition for a new military avionics product, it

can expect to receive follow-on orders for added quantities in future years, provided technical performance is adequate and price does not increase more than is justifiable as being due to inflation. Given the nature of Government contracts and the limitations imposed on profits, competition provides contractors with the only real incentive to reduce costs and thus prices. In the absence of product standardization (i.e., form, fit, and function standards), there can be little meaningful continuing competition, and premium prices are paid to a sole source. While this pattern of action can sometimes result in minimum life cycle costs to the Government, it should not be accepted automatically as the normal way of doing business. Future designs for common avionics equipment should be required to meet form, fit, and function standards. This would permit effective production competition, when warranted, and would also simplify future equipment retrofits. Further, even without competition, increased standardization is conducive to greater productivity. Sellers (particularly those seeking sole source contracts) should concentrate on demonstrating their ability to reduce costs and willingness to reduce prices even in the absence of competition.

With respect to technology, investment in research and development provides a competitive edge to firms competing in consumer and industrial markets. Although the Government funds much military research and development, firms competing for military business should likewise seek a competitive edge by investing their own resources, both in anticipatory pre-proposal work and in more formalized independent research and development. Greater emphasis should be placed by both Government and

industry on upgrading and improving process technology, since productivity enhancement is largely dependent on increasingly efficient production processes. With respect to market share, defense industry firms should capitalize on sole source opportunities, but recognize that a demonstrated willingness to reduce costs even in the absence of competition will carry political weight influencing future sole source awards.

Experience curve theory for consumer and industrial products advocates capturing the growth in markets, rather than attempting to displace the market share of established producers. For defense industry firms, this is most easily done by becoming established as the initial (if possible, sole source) producer. However, there are also profit opportunities for capable producers who are not initial producers. The Government sometimes seeks to develop alternative sources for critical products to maintain flexibility, rather than to obtain immediate price competition. Production oriented firms in particular should seek out such second source opportunities, concentrating on adding to their assortment those products which are compatible with already developed and established process technology. The combination of process compatability and initial lack of emphasis on price should allow them to overcome the experience advantage of the original source, and prepare for future price-based competitions.

New products are introduced in the military market place for a variety of reasons: primarily to meet operational needs, but also to increase flexibility and to maintain innovative capabilities. For the Government to realize greater productivity gains, standardization

should be increased, and design changes and new product introductions should be reduced. Defense industry firms should become thoroughly familiar with life cycle cost methodology (to include the use of price experience curves in projecting future prices), and should place increased emphasis on the expected life cycle cost advantages of proposed new products which they are marketing.

Perhaps the greatest opportunity for the Government to capitalize on experience curve theory lies in the area of procurement planning and negotiations. Prior to the initial production of new products, life cycle cost estimates should be developed (using experience curve theory to forecast future acquisition prices) for such alternative procurement approaches as no competition, competition for initial production only, and continuing competition (i.e., maintaining at least two sources). The approach which minimizes the expected life cycle cost to the Government should then be implemented, provided it does not unduly restrict industrial flexibility and innovative capability. Experience curve based on price projections can also be of particular value in preparing for negotiations for follow-on procurements of established products. While being generally guided by such projections, both Government and industry negotiators will also need to be completely familiar with factors influencing experience realization, providing a basis for negotiation of variances from price projections. (This is not advocating conducting negotiations based solely on price projections, but rather introducing such considerations as an added dimension to negotiations.)

Shifting now to a focus on buyer-seller interactions, consider first Government interventions in production contracts. The extent of Government intervention in contractor decisions appears to be partly responsible for the relatively gradual rate of experience realization in military procurements. Productivity should increase if interventions are reduced; overcontrol is counterproductive. For instance, designs should be required to meet form, fit, and function standards, with the contractor being free to make changes to improve producibility (provided the standards are still met). Form, fit, and functional capabilities should not be changed once production specifications have been agreed upon, except for cases of overriding military urgency (e.g., "nice-to-have" but non-essential features should not be added). Producers can help themselves as well as the Government by identifying areas in which reduced Government intervention could increase productivity.

Producer risks are also unique in the defense market place. Through funding most research and development, providing or paying for specialized tools and test equipment, and in some cases providing plant facilities for contractor use, the Government seeks to minimize some of the risks to which contractors are subjected. However, other risks remain, most notably due to market uncertainties. Orders are placed at irregular intervals, and for varying and often unpredictable quantities. Due to changing military priorities and close Congressional control of funds, there is often uncertainty even as to whether or not there will be a next order. Uncertainties such as these confound a contractor's efforts to build, train, and maintain a stable, experienced work force.

They also serve as a disincentive to investments in process improvements, resulting in lost opportunities for gains in experience. Extended multiple-year production plans, bearing tentative Congressional approval when appropriate, should be shared with prospective contractors. Delivery schedules should be developed in cooperation with producers to minimize workforce turbulence. Producers can again help themselves by identifying the risks and uncertainties which are of greatest concern to them.

Incentives should be provided to encourage contractors to manage efficiently, with emphasis on achievable rewards, not just on penalties. Reduced Government intervention will mean greater responsibilities for producers, which should be recognized in the incentive structure. Both the Government and producers should ensure that all personnel who could reasonably be expected to influence the distribution of incentives are at least aware of the incentive structure. In particular, they should understand the ways in which they, as individuals, can affect the distribution of incentives. (The experience effect does not guarantee that productivity gains will be realized. Productivity enhancement will only result when individuals have the incentive, as well as the ability and opportunity, to make them happen.)

Finally, the catch-all category of productivity inhibitors deserves further attention. Several have already been identified, including excessive Government interventions, market uncertainties, and lack of real incentives. As observed in the present research, various production parameters also affect costs and thus price. Productivity will benefit from improved (two-way) communications between producers and

the Government, especially during the development of production plans. Opportunities for productivity increases abound, but aggressive management is needed to convert the opportunities into realized productivity gains.

The experience curve effect provides a powerful tool for use by both Government and industry in a variety of applications. It can help contractors increase profits, and at the same time help Government procurement decision makers in maximizing the return on their expenditures of taxpayers' dollars. While it is no panacea, it is well worth understanding and applying.

BIBLIOGRAPHY

BIBLIOGRAPHY

NOTE: Documents available from the National Technical Information Service (Defense Documentation Center) are identified by AD numbers. Documents available from the Defense Logistics Studies Information Exchange are identified by LD numbers.

Abernathy, William J. The Productivity Dilemma: Roadblock to Innovation in the Automobile Industry. Boston: Harvard University, April 1976.

Abernathy, William J., and Kenneth Wayne. "Limits of the Learning Curve," Harvard Business Review, Vol. 52, No. 5, pgs 109-119, SEP-OCT 1974.

Aeronautical Systems Division. "ASD Cost Escalation Report Number 110-C: Historical and Forecasted Aeronautical Cost Indices," Wright-Patterson Air Force Base, Ohio, April 1976.

Andress, Frank J. "The Learning Curve as a Production Tool," Harvard Business Review, Vol. 32, No. 1, pgs 87-97, JAN-FEB 1954.

Anthony, Robert N. Management Accounting Principles, Revised Edition. Homewood, IL: Richard D. Irwin, Inc., 1970.

Anthony, Robert N. Management Accounting: Text and Cases, 3rd Edition. Homewood, IL: Richard D. Irwin, Inc., 1965.

Arditti, Fred D., "On the Separation of Production from the Developer," Santa Monica, CA: RAND Corp., May 1967. P-3542-1.

Asher, Harold. Cost-Quantity Relationships in the Airframe Industry. Santa Monica, CA: RAND Corp., 1 July 1956. R-291. AD 105540.

Baloff, Nicholas. Manufacturing Start-Up: A Model. Stanford: Stanford University, 1963. PHD Dissertation.

Baloff, Nicholas. "Start-Ups in Machine-Intensive Production Systems," Journal of Industrial Engineering, Vol. 17, No. 1, January 1966.

Barrett, Charles Francis. An Empirical Analysis of Learning Curves. Buffalo: State University of New York, May 1969. PHD Dissertation. Wright-Patterson Air Force Base, Ohio: Air Force Institute of Technology, NOV 1970. AFIT TR 70-7. AD 877042.

Batchelder, C. A.; H. E. Boren, Jr.; H. G. Campbell; J. A. DeiRossi; & J. P. Large. An Introduction to Equipment Cost Estimating. Santa Monica, CA: RAND Corp., DEC 1969. RM-6103-SA. AD 702424.

Bernard, Harvey Della. "New Wrinkles in Improvement Curves," Defense Management Journal, Vol. 10, No. 2, pgs 49-54, APR 1974. LD 30918.

Berry, F. Clifton, Jr. "The FY77 Defense Budget: Adding Teeth to the Navy, Reducing Tail in the Air Force," Armed Forces Journal International, FEB 1976.

Blinn, Donald E., and William D. Yri. Acquisition Management of Common Avionics in the United States Air Force. Wright-Patterson Air Force Base, Ohio: Air Force Institute of Technology, SEP 1975. GSM/SM75D-12.

Booz-Allen Applied Research, Inc. "Development of Acquisition Cost Model," Washington, D.C., 22 DEC 1969. AD 878090.

Boren, H. E., Jr., and H. G. Campbell. Learning Curve Tables: Volume I, 55-69 Percent Slopes. Santa Monica, CA: RAND Corp., April 1970. RM-6191-PR(V2). AD 708714.

Boren, H. E., Jr., and H. G. Campbell. Learning Curve Tables: Volume III, 86-99 Percent Slopes. Santa Monica, CA: RAND Corp., April 1970. RM-6191-PR(V3). AD 709178.

Boston Consulting Group Staff. Perspectives on Experience. Boston, JAN 1972.

Brewer, Glenn M. The Learning Curve in the Airframe Industry. Wright-Patterson Air Force Base, Ohio: Air Force Institute of Technology, AUG 1965. SLSR-18-65. AD 012250.

Brockman, William Francis, and Freddie Dale Dickens. Investigation of Learning Curve and Cost Estimation Methods for Cargo Aircraft. Wright-Patterson Air Force Base, Ohio: Air Force Institute of Technology, DEC 1967. GSM/SM/67-2/7. AD 665464.

Buck, James R.; Jose M. A. Tanchoco; & Arnold L. Sweet. "Parameter Estimation Methods for Discrete Exponential Learning Curves," AIEE Transactions, Vol. 8, No. 2, pgs 184-194, JUN 1976.

Burns, Jewel Ralph. "A Comparison of Two Methods for Predicting Loss of Learning Due to a Break in Production," Texarkana, TX: Red River Army Depot, MAR 1976. AD A024814. LD 36272A.

Carlson, J. G. H. "Learning, Lost Time, and Economic Production (The Effect of Learning on Production Lots)," Production and Inventory Management, 4th Quarter 1975, pgs 21-33.

Carlson, John G., and Alan J. Rowe. "How Much Does Forgetting Cost?", Industrial Engineering, SEP 1976, pgs 40-47.

Colasuonno, Vincent. An Analysis of Progress Curve Conceptual Advances and Progress Curve Uses, Since 1956. Wright-Patterson Air Force Base, Ohio: Air Force Institute of Technology, SEP 1967. GSM/SM/67-5. AD 664952.

Conley, Patrick. "Experience Curves as a Planning Tool," IEEE Spectrum, Vol. 7, No. 6, pgs 63-68, June 1970.

Conrad, Robert Ballard. Intermittent Interference with Pseudo-Repetitive Operations and Its Effect on Standard Time and the Learning Curve. Chapel Hill, NC: University of North Carolina, 1969. PHD Dissertation.

Conway, R. W., and Andrew Schultz, Jr. "The Manufacturing Progress Function," Journal of Industrial Engineering, Vol. 10, No. 1, JAN-FEB 1959.

Dahlhaus, Frank J., and Joseph S. Roj. Learning Curve Methodology for Cost Analysts. Washington: Army Materiel Command, OCT 1967. AD 661052.

Daniels, James M. "Estimating Avionics Equipment Costs for Military Aircraft," Washington: Chief of Naval Operations, 13 DEC 1974. AD 408232.

Fazio, Peter F., and Stephen H. Russell. An Analytical Approach to Optimizing Airframe Production Costs as a Function of Production Rate. Wright-Patterson Air Force Base, Ohio: Air Force Institute of Technology, JAN 1974. SLSR 30-74A. AD 775698.

Fisher, Douglas H. Production Cost Management. Maxwell Air Force Base, Alabama: Air University, May 1976. AD B011898L.

Gibson, Weldon B. Acceleration of Airframe Production as a Function of Direct Labor Application and Productivity. Stanford: Stanford University, OCT 1949. PHD Dissertation.

Gossett, James L. "Variations Intercepting Experience," Redstone Arsenal, Alabama: Army Missile Command, JAN 1971. AD 721666.

Harris, Robert A.; Wayne L. Jones; Eddie G. Hammons; & J. M. Fleener. Alpha and Omega and the Experience Curve. Redstone Arsenal, Alabama: Army Missile Command, 12 April 1965. AD 617133.

Hartung, Walter G. "Cost Estimate Errors Resulting from the Use of Learning Curve Methods," Hanscom Air Force Base, MA: Electronic Systems Division, AUG 1969. ESD-TR-69-295. AD 859698.

Hartung, Walter G. "Estimating Learning Curve Cost Errors," Proceedings of the Fifth Annual Department of Defense Cost Research Symposium, Volume 1. Washington: Office of the Assistant Secretary of Defense (Systems Analysis), pgs 251-276, 24 & 25 MAR 1970. AD 875742.

Hirschmann, Winfred B. "Profit from the Learning Curve," Harvard Business Review, Vol. 42, No. 1, JNA-FEB 1964.

Hoffmann, Thomas R. "Effect of Prior Experience on Learning Curve Parameters," Journal of Industrial Engineering, Vol. 19, No. 8, pgs 412-413, AUG 1968.

Ilderton, Robert Blair. Methods of Fitting Learning Curves to Lot Data Based on Assumptions and Techniques of Regression Analysis. Washington: George Washington University, August 1970. AD A011583.

Jain, Subhash. "Translating Experience into Growth," Managerial Planning, MAR-APR 1975, pgs 1-5+.

James, Paul Meyer. "Derivation and Application of Unit Cost Expressions Perturbed by Design Changes," Naval Research Logistics Quarterly, Vol. 15, No. 3, pgs 459-468, SEP 1968. AD 676409. LD 18974.

Jones, Wayne L. The Experience Curves: Volume I, 67% Through 84%. Redstone Arsenal, Alabama: Army Missile Command, SEP 1962. AD 612803.

Jones, Wayne L. The Experience Curves: Volume II, 85% Through 99%. Redstone Arsenal, Alabama: Army Missile Command, SEP 1962. AD 612804.

Karsch, O. Arthur. "A Least Squares Comparison for Learning Curve and Sizing Slope Problems," Wright-Patterson Air Force Base, Ohio: Aeronautical Systems Division, FEB 1971. ASD/XR 71-1. AD 731175.

Keachie, E. C. Manufacturing Cost Reduction Through the Curve of Natural Productivity Increase. Berkeley: University of California, 1964.

Kelley, Robert W. "Value Engineering and Experience Curve Predictions," Redstone Arsenal, Alabama: Army Missile Command, 10 SEP 1965. AD 625984.

Kiefer, Lawrence A. "Tables for Approximation of Completion Versus Expenditures for Log Log Learning Curves," St. Louis, MO: Army Aviation Systems Command, FEB 1969. USA AVSCOM TR 69-1. AD 848154L.

Kotler, Philip. Marketing Management: Analysis, Planning, and Control, 2nd Edition. Englewood Cliffs, NJ: Prentice-Hall, Inc., 1972.

Large, Joseph P.; Karl Hoffmayer; & Frank Kontrovich. Production Rate and Production Cost. Santa Monica, CA: RAND Corp., DEC 1974. R-1609-PA&E. AD A009074.

Lemke, B. C., and James Don Edwards (eds). Administrative Control and Executive Action. Columbus, OH: Charles E. Merrill Books, Inc., 1961.

Malstrom, Eric Michael. Adaptive Forecasting of Project Costs and Throughput Times in a Job Shop Production Facility. West Lafayette, IN: Purdue University, 1974. PHD Dissertation.

Morse, Wayne John. The Allocation of Production Costs with the Use of Learning Curves. East Lansing, MI: Michigan State University, 1971. PHD Dissertation.

Nie, Norman H.; C. Hadlai Hull; Jean G. Jenkins; Karin Steinbrenner; & Dale H. Bent. SPSS: Statistical Package for the Social Sciences, 2nd Edition. New York: McGraw-Hill Book Company, 1975.

Niebel, Benjamin W. Motion and Time Study, 5th Edition. Homewood, IL: Richard D. Irwin, Inc., 1974.

Orsini, Joseph A. An Analysis of Theoretical and Empirical Advances in Learning Curve Concepts Since 1966. Wright-Patterson Air Force Base, Ohio: Air Force Institute of Technology, March 1970. GSA/SM/70-12. AD 875892.

Pegels, C. Carl. "Start Up or Learning Curves - Some New Approaches," Decision Sciences, Vol. 7, No. 4, pgs 705-713, OCT 1976.

Pichon, Allen A., and Charles L. Richardson. The Development of a Predictive Model for First Unit Costs Following Breaks in Production. Wright-Patterson Air Force Base, Ohio: Air Force Institute of Technology, AUG 1974. SLSR #15-74B. AD 785953.

Puryear, Van A. "New Progress Functions - With Probability Modifiers," St. Louis, MO: Army Troop Support Command, 9 May 1973. AD 763830.

Puryear, Van A. "The Progress Function: Analysis and Application for the Acquisition Process," St. Louis, MO: Army Mobility Equipment Command, 20 DEC 1972. AD 908621L.

Reguero, Miguel Angel. An Economic Study of the Military Airframe Industry. Wright-Patterson Air Force Base, Ohio: Air Materiel Command (now Air Force Logistics Command), OCT 1957.

Scherer, Frederic M. The Weapons Acquisition Process: Economic Incentives. Boston: Harvard University, 1964.

Schumacker, Robert Louis. Factors Affecting the Improvement Curve in a Labor-Intensive Manufacturing Organization. Seattle: University of Washington, 1968. PHD Dissertation.

Smith, Larry Lacross. An Investigation of Changes in Direct Labor Requirements Resulting from Changes in Airframe Production Rate. Eugene, Oregon: University of Oregon, June 1976. PHD Dissertation.

Spencer, Edson W. "Tough Customer: Selling Uncle Sam," MBA, FEB 1977, pgs 48-50.

Tilles, S. "Making Strategy Explicit," Business Strategy, H. Igor Ansoff, editor. Baltimore: Penguin Books, 1974.

Ulsamer, Edgar. "USAF's Crusade to Streamline Industrial Production," Air Force Magazine, Vol. 59, No. 10, pgs 62-67, OCT 1976.

Waggoner, Larry P. "Army Materiel Experience Curve Guideline," Aberdeen Proving Ground, MD: Army Materiel Systems Analysis Agency, July 1971. AMSAA TM-113. AD 887204L.

Woolley, Kenneth Musser. Experience Curves and Their Use in Planning. Stanford: Stanford University, May 1972. PHD Dissertation.

Wortham, A. W., and R. B. Misra. "A Note on the Theory of Learning Curve Relations," The Logistics and Transportation Review, Vol. 8, No. 1, pgs 83-88, 1972. LD 27828.

Wright, T. P. "Factors Affecting the Cost of Airplanes," Journal of the Aeronautical Sciences, Vol. 3, FEB 1936.

General References

Aitchison, J., and J. A. C. Brown. The Lognormal Distribution. Cambridge, GB: University Press, 1957.

ARINC Research Corp. Air Force Avionics Standardization: An Initial Investigation into an ASD INS Procurement Concept (Final Report). Annapolis, MD, May 1976. #1269-01-2-1497.

Baloff, Nicholas. "Extension of the Learning Curve - Some Experimental Results," Operational Research Quarterly, Vol. 22, No. 4, DEC 1971.

Baloff, Nicholas. "Startup Management," IEEE Transactions on Engineering Management, Vol. EM-17, No. 4, NOV 1970.

Baumol, William J. Economic Theory and Operations Analysis, 2nd Edition. Englewood Cliffs, NJ: Prentice-Hall, 1965.

Boston Consulting Group Staff. Perspectives on Corporate Strategy. Boston, 1968.

Brenneck, R. "The Learning Curve for Labor Hours - For Pricing," National Association of Accountants Bulletin, June 1958.

Bright, Boris E., and Bernard List. Aircraft Avionics (Digital Avionics Study) Final Report, Volume I. Wright-Patterson Air Force Base, Ohio: Aeronautical Systems Division, April 1973. ASD-TR-73-18.

Canova, J. "Two Ways to Use the Learning Curve," Purchasing, March 1965.

Carrier, J. M., and R. W. Smith. "Aircraft Airframe Cost Estimating Techniques," Chapter IX in Concepts and Procedures of Cost Analysis, J. P. Large, editor. Santa Monica, CA: RAND Corp., June 1963. RM-3589-PR. AD 411554.

Cooley, William W., and Paul R. Lohnes. Multivariate Data Analysis. New York: John Wiley & Sons, 1971.

Dixon, Wilfrid J., and Frank J. Massey, Jr. Introduction to Statistical Analysis, 2nd Edition. New York: McGraw-Hill, 1957.

Fisher, G. H. "Use of Statistical Regression Analysis in Deriving Estimating Relationships," Chapter V in Concepts and Procedures of Cost Analysis, J. P. Large, editor. Santa Monica, CA: RAND Corp., June 1963. RM-3589-PR. AD 411554.

Goel, S. N., and R. H. Becknell. "Learning Curves That Work," Journal of Industrial Engineering, Vol. 4, No. 5, May 1972.

Hall, L. H. "Experience with Experience Curves for Aircraft Design Changes," National Association of Accountants Bulletin, DEC 1957.

Henderson, James M., and Richard E. Quandt. Microeconomic Theory: A Mathematical Approach. New York: McGraw-Hill, 1958.

Hirsch, W. Z. "Manufacturing Progress Functions," in Analysis of Industrial Operations, E. H. Bowman and R. B. Fetter, editors. Homewood, IL: Richard D. Irwin, Inc., 1959.

Holdham, J. H. "Learning Curves - Their Applications in Industry," Production and Inventory Management, Vol. 11, No. 4, 4th Quarter 1970.

Johnson, George V. "On Predicting Production Costs and Probable Learning Rates from R&D Investments by S-Curve/Learning Curve Relationships," St. Louis, MO: Army Mobility Equipment Command, OCT 1969. AD 750098.

Johnston, J. Econometric Methods, 2nd Edition. New York: McGraw-Hill, 1972.

Kottler, J. L. "The Learning Curve - A Case History in Its Application," Journal of Industrial Engineering, Vol. 15, JUL-AUG 1964.

Large, J. P. An Introduction to Equipment Cost Estimating. Santa Monica, CA: RAND Corp., JAN 1968. RM-5470-SA. AD 664825.

Lewis, Howard T., and Wilbur B. England. Procurement: Principles and Cases, 3rd Edition. Homewood, IL: Richard D. Irwin, 1957.

Logistics Management Institute. Multi-Year Procurement and Learning Curve Effects. Washington, October 1967.

Mantell, Leroy H. "Some Estimates of Returns to Scale in the Telephone Industry," IEEE Transactions on Systems, Man, and Cybernetics, Vol. SMC-5, No. 1, JAN 1975.

Morrison, Donald F. Multivariate Statistical Methods. New York: McGraw-Hill, 1967.

Peck, Merton J., and Frederic M. Scherer. The Weapons Acquisition Process: An Economic Analysis. Boston: Harvard University, 1962.

Press, S. James. Applied Multivariate Analysis. New York: Holt, Rinehart and Winston, 1972.

RAND Corporation. Military Equipment Cost Analysis. Santa Monica, CA, June 1971. AD 901477L.

Ruskin, Arnold M., and Robert Lerner. "Forecasting Costa and Completion Dates for Defense Research and Development Contracts," IEEE Transactions on Engineering Management, Vol. EM-19, No. 4, NOV 1972.

Samuelson, Paul A. Economics: An Introductory Analysis, 3rd Edition. New York: McGraw-Hill, 1955.

Schweder, Tore. "Some 'Optimal' Methods to Detect Structural Shift or Outliers in Regression," American Statistical Association Journal, Vol. 71, No. 354, pgs 491-501, June 1976.

Scientific Advisory Board, USAF. "Report of the USAF Scientific Advisory Board Guidance and Control Panel Review of Aircraft Inertial Systems," Washington, March 1975.

Smith, S. B. "The Learning Curve - Basic Purchasing Tool," Purchasing, March 1965.

Spurr, William A.; Lester S. Kellogg; & John H. Smith. Business and Economic Statistics. Homewood, IL: Richard D. Irwin, 1955.

Theil, Henri. Applied Economic Forecasting. Chicago: Rand-McNally, 1966.

Trueger, Paul M. Accounting Guide for Defense Contracts, 6th Edition. New York: Commerce Clearning House, Inc., 1971.

Welkowitz, Joan; Robert B. Ewen; & Jacob Cohen. Introductory Statistics for the Behavioral Sciences. New York: Academic Press, 1971.

Witt, Hugh E., and James T. Lynn. "Circular No. A-109: Major Systems Acquisitions," Washington: Office of Management and Budget, 5 April 1976.

Wyer, R. "Learning Curve Helps Figure Profits, Control Costs," National Association of Accountants Bulletin, DEC 1953.

Yelle, Louis E. "Technological Forecasting: A Learning Curve Approach," Industrial Management, JAN 1974.

APPENDICES

APPENDIX A

B VALUES FOR VARIOUS SLOPES

The material presented in this appendix is first cited on page 22.

TABLE A1 - B VALUES FOR VARIOUS SLOPES

Slope (%)	B Value	Slope (%)	B Value
50	-1.00000	85	-.23447
51	-.97143	86	-.21759
52	-.94342	87	-.20091
53	-.91594	88	-.18442
54	-.88897	89	-.16812
55	-.86250	90	-.15200
56	-.83650	91	-.13606
57	-.81097	92	-.12029
58	-.78588	93	-.10470
59	-.76121	94	-.08927
60	-.73697	95	-.07400
61	-.71312	96	-.05889
62	-.68966	97	-.04394
63	-.66658	98	-.02915
64	-.64386	99	-.01450
65	-.62149	100	.00000
66	-.59946	101	.01436
67	-.57777	102	.02857
68	-.55639	103	.04264
69	-.53533	104	.05658
70	-.51457	105	.07039
71	-.49411	106	.08406
72	-.47393	107	.09761
73	-.45403	108	.11103
74	-.43440	109	.12433
75	-.41504	110	.13750
76	-.39593	111	.15056
77	-.37707	112	.16350
78	-.35845	113	.17632
79	-.34008	114	.18903
80	-.32193	115	.20163
81	-.30401	116	.21412
82	-.28630	117	.22651
83	-.26882	118	.23879
84	-.25154	119	.25096

APPENDIX B

INFLATION DEFLATORS

The material presented in this appendix is first cited on page 128.

TABLE A2 - INFLATION DEFLATORS

Year	AVPR Factor	FPGS Factor	GNP Factor
1960	.478	.467	.556
1961	.494	.471	.563
1962	.508	.473	.569
1963	.525	.483	.576
1964	.537	.506	.586
1965	.553	.517	.597
1966	.571	.532	.613
1967	.608	.543	.633
1968	.645	.565	.658
1969	.683	.603	.690
1970	.724	.670	.727
1971	.763	.721	.762
1972	.802	.769	.786
1973	.853	.814	.831
1974	.929	.901	.915
1975	1.000	1.000	1.000
1976 *	1.069	1.058	1.051

AVPR = Avionics Procurement

FPGS = Federal Purchases of Goods and Services

GNP = Gross National Product

* Preliminary estimates.

Sources: Derived from information in the Survey of Current Business and Aeronautical Systems Division Comptroller Report Number 110-C.

NOTE: Divide "Then-Year" Dollars by Deflator to Normalize to 1975.

APPENDIX C

AVIONICS PRICE EXPERIENCE CURVES

The cumulative average theory price experience curves for each of the 32 avionics data item-contractor and item-industry subfiles are presented on the following pages. Federal Purchases of Goods and Services (FPGS) deflators were used to adjust then-year dollars to constant dollars referenced to the base year 1975. In these computer generated plots, asterisks represent individual plot points. Digits appearing in lieu of asterisks, such as "2," "4," or "3" in Figure A1, represent the number of plot points overlaid at one location due to insufficient graphic resolution. For all plots, the vertical scale is the natural logarithm of cumulative average unit price, and the horizontal scale is the natural logarithm of cumulative quantity. The material presented in this appendix is first cited on page 105, and again on page 129.

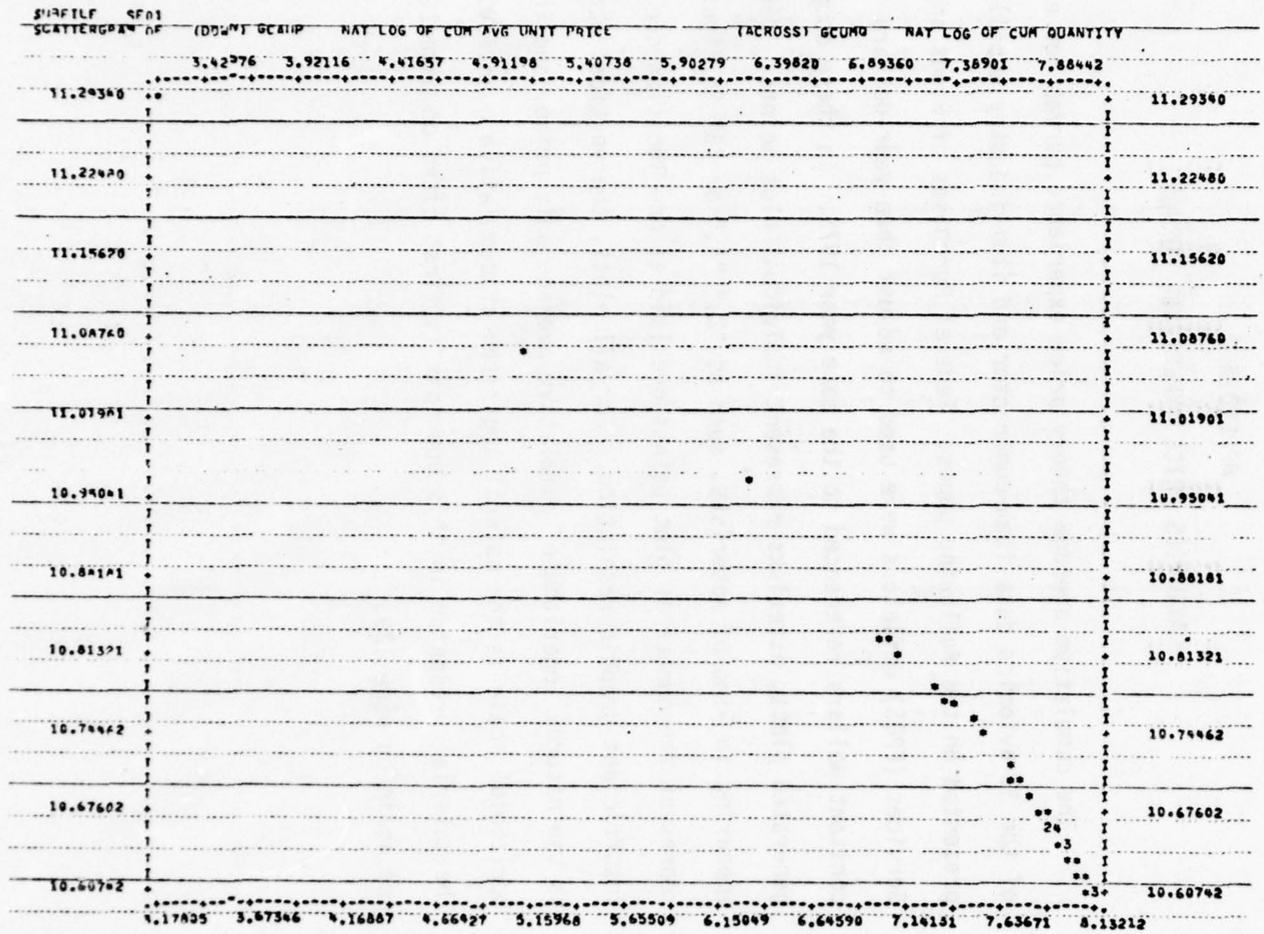


FIGURE A1 - PRICE EXPERIENCE CURVE, SUBFILE 01

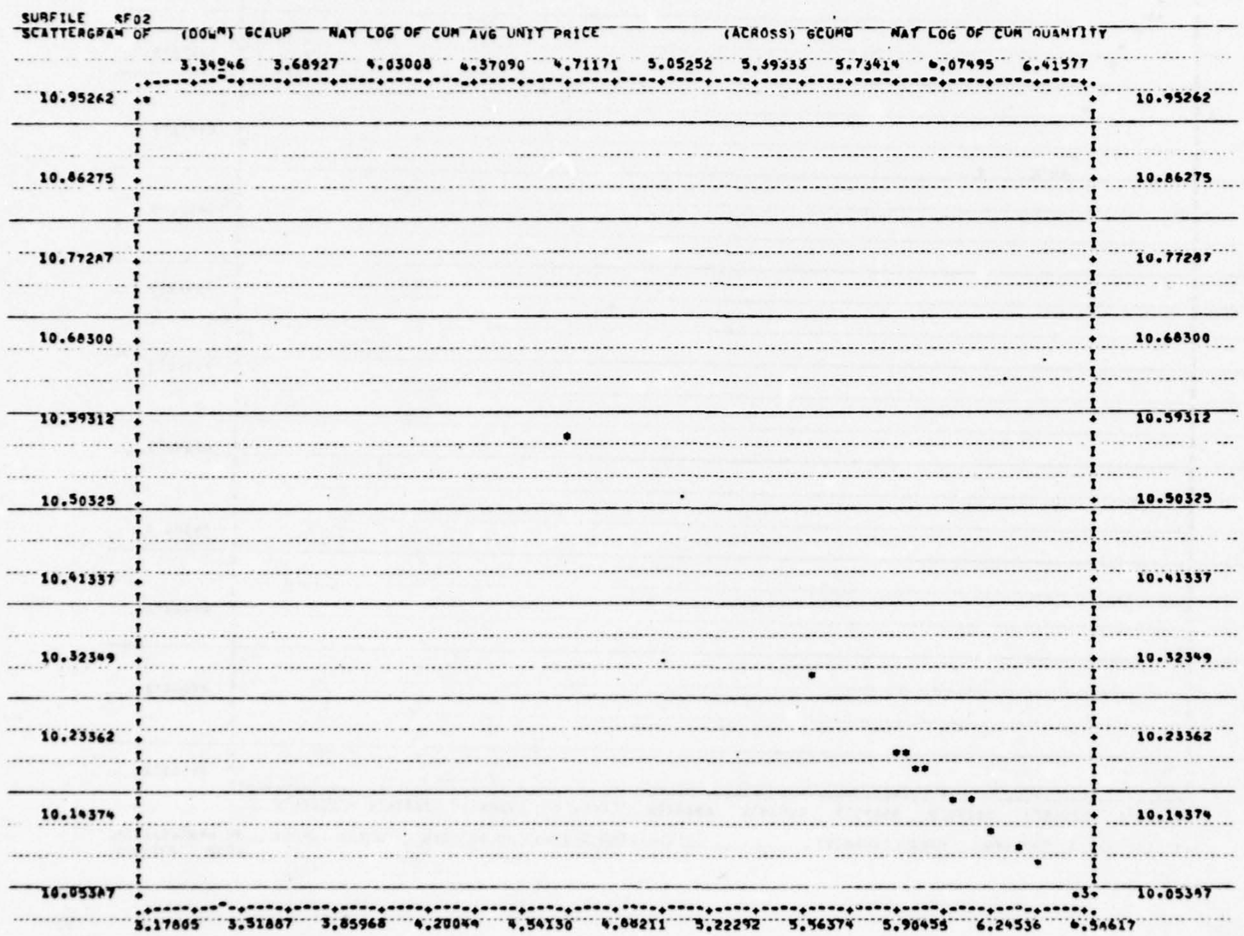


FIGURE A2 - PRICE EXPERIENCE CURVE, SUBFILE 02

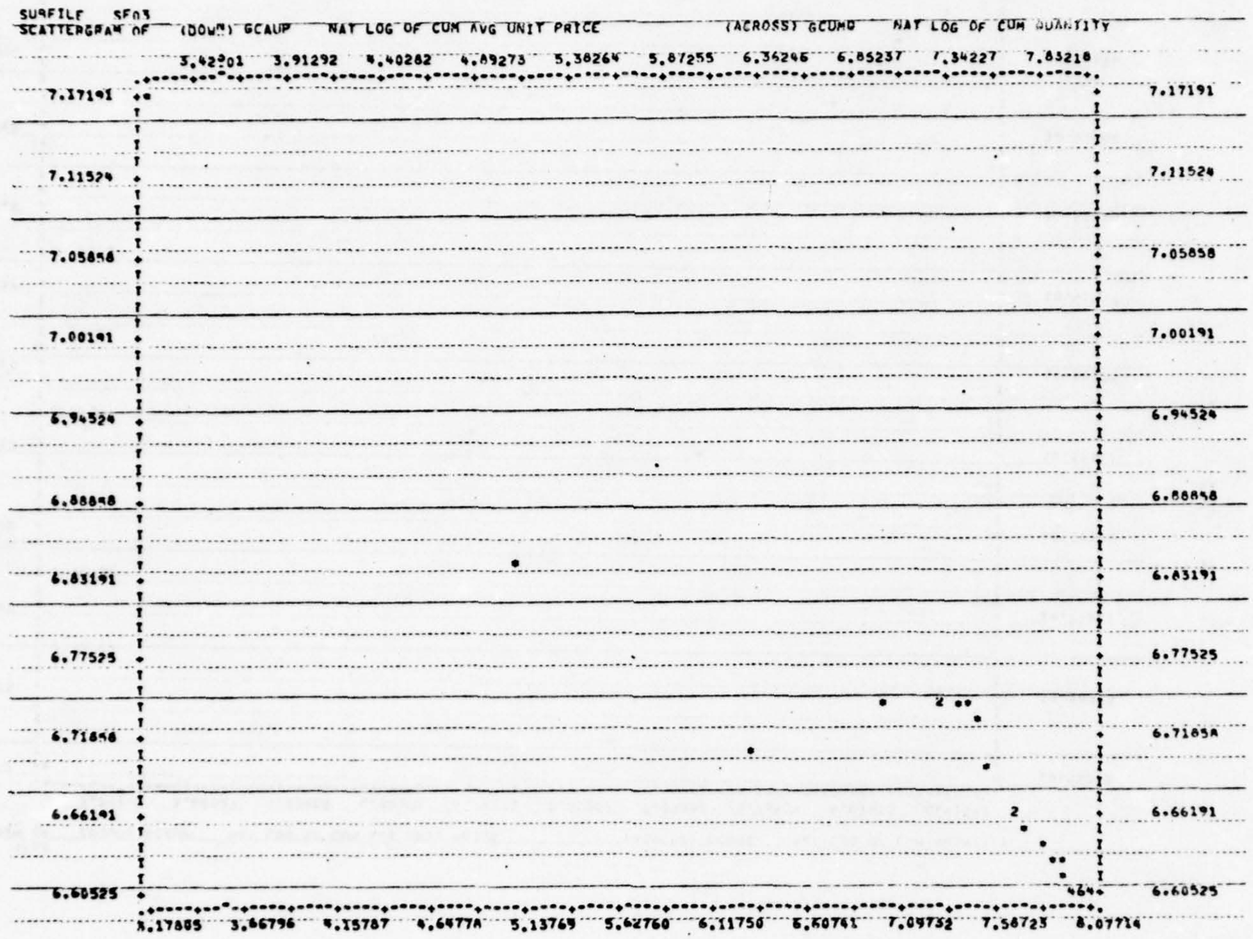


FIGURE A3 - PRICE EXPERIENCE CURVE, SUBFILE 03

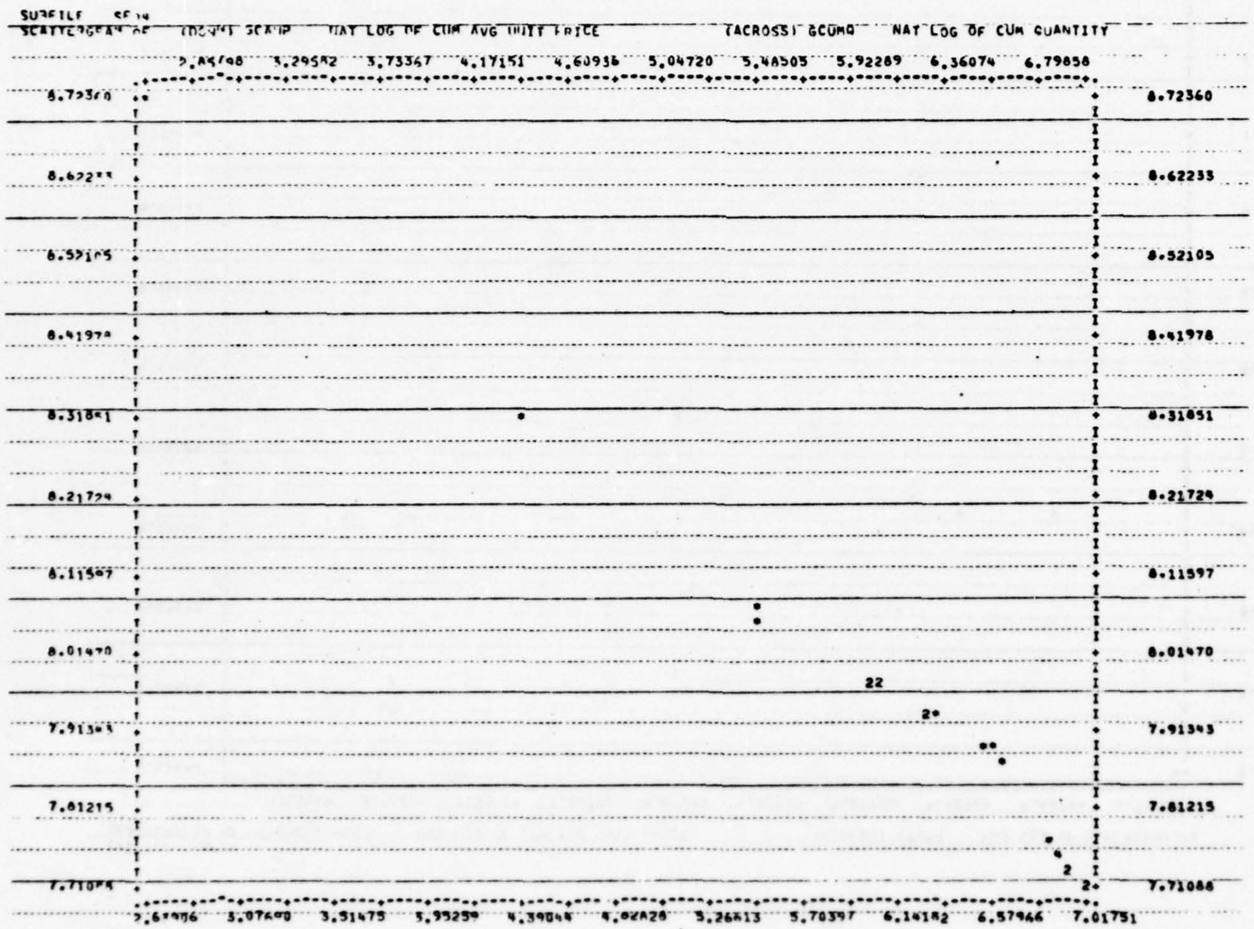


FIGURE A4 - PRICE EXPERIENCE CURVE, SUBFILE 04

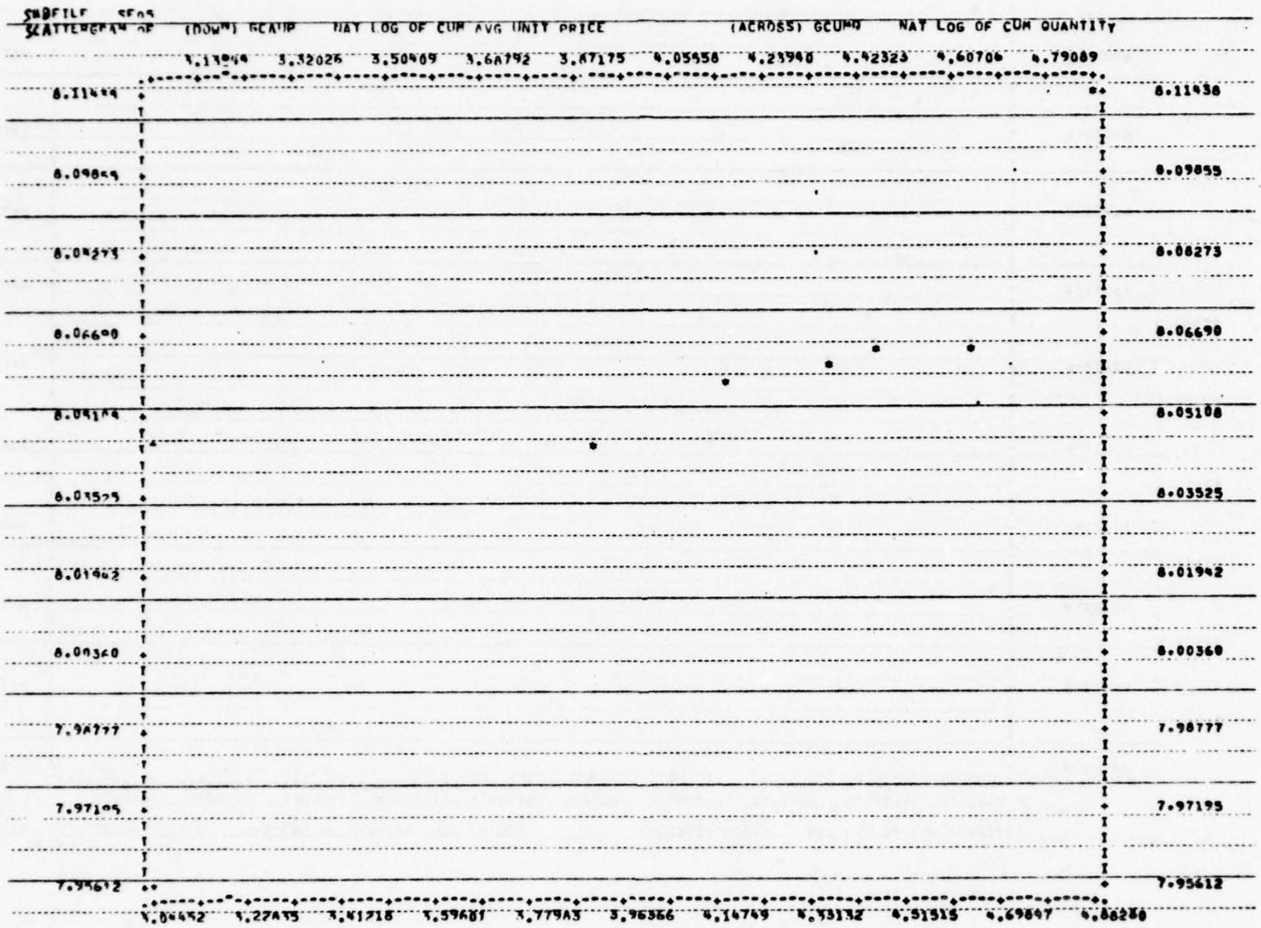


FIGURE A5 - PRICE EXPERIENCE CURVE, SUBFILE 05

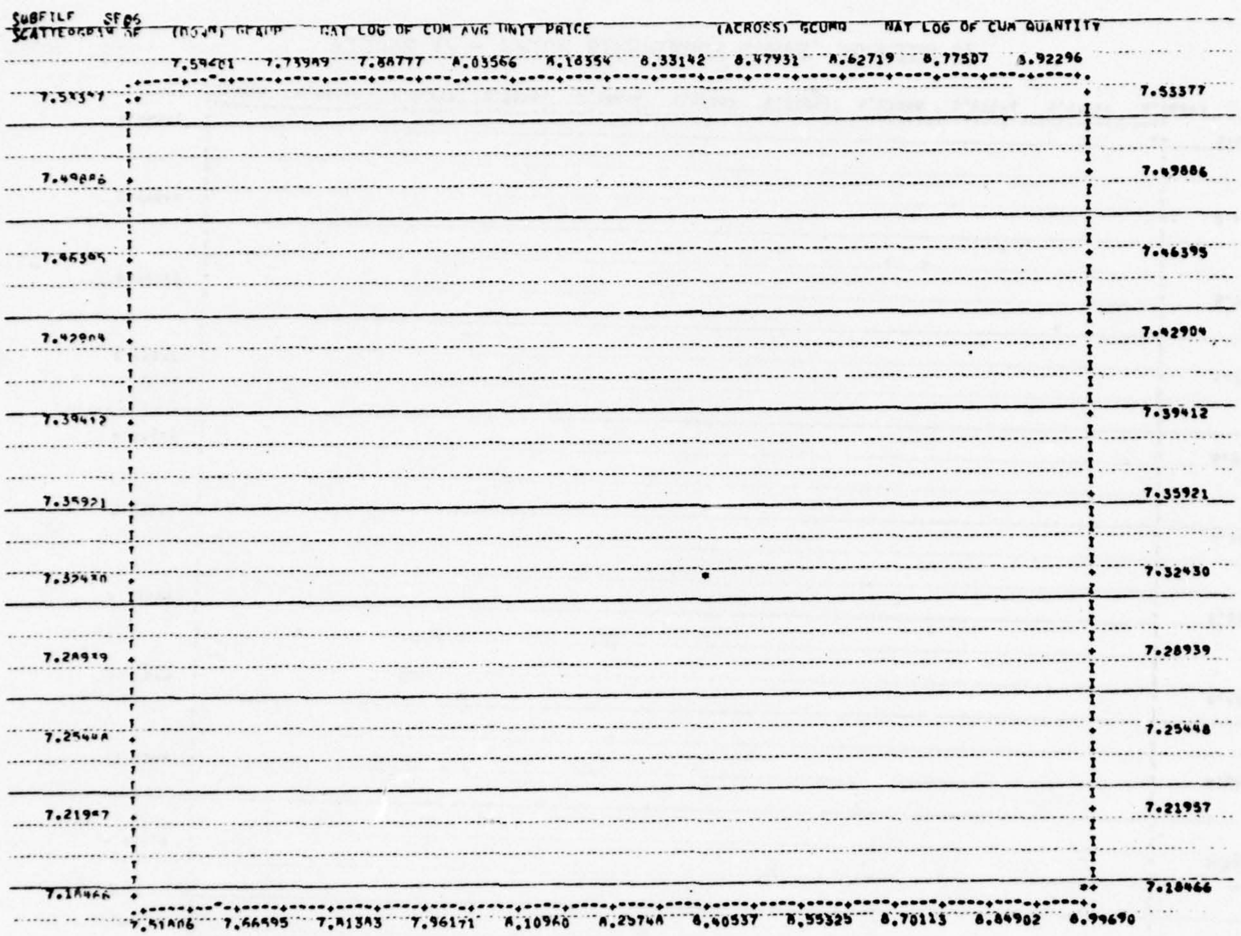


FIGURE A6 - PRICE EXPERIENCE CURVE, SUBFILE 06

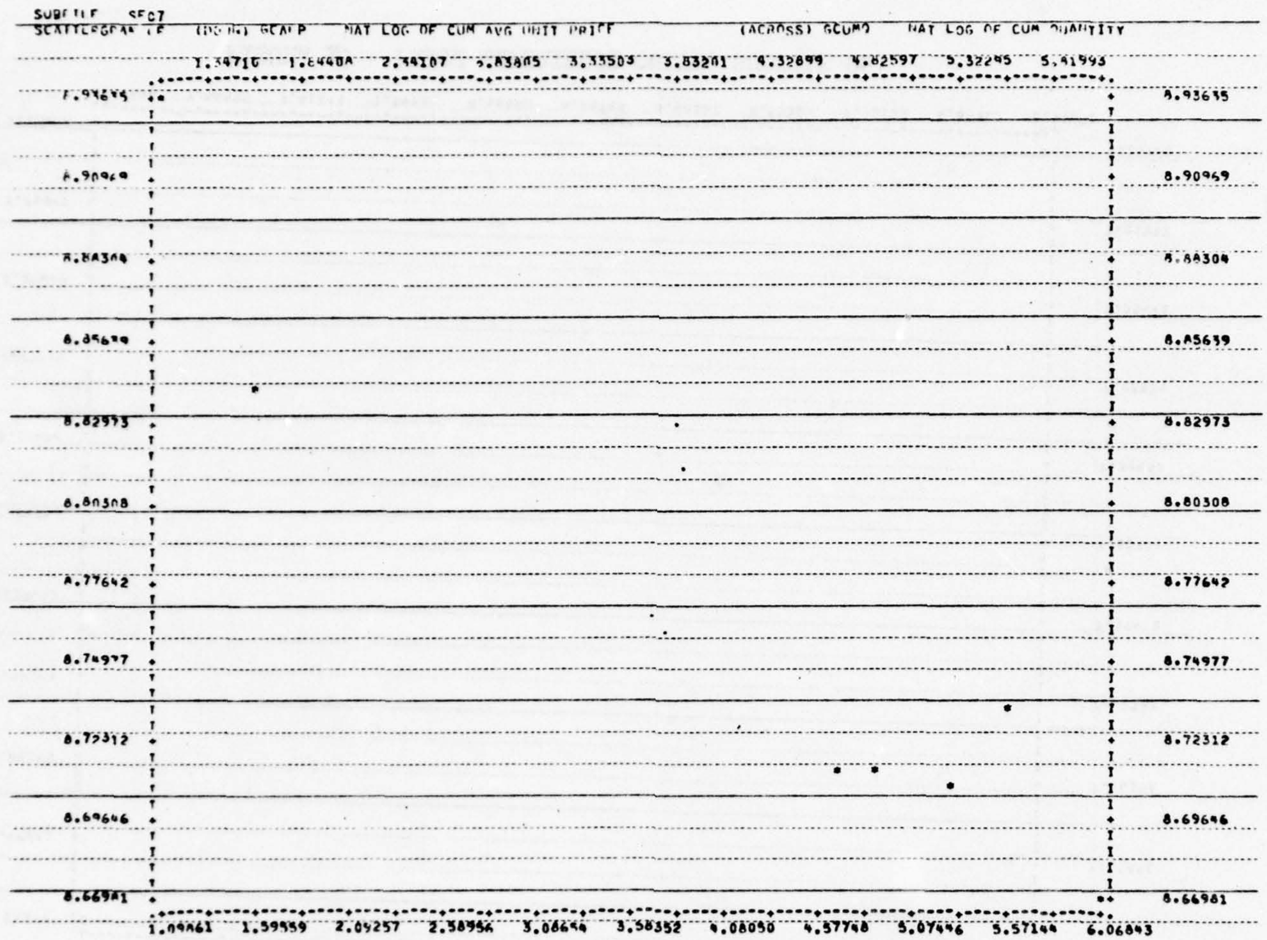


FIGURE A7 - PRICE EXPERIENCE CURVE, SUBFILE 07

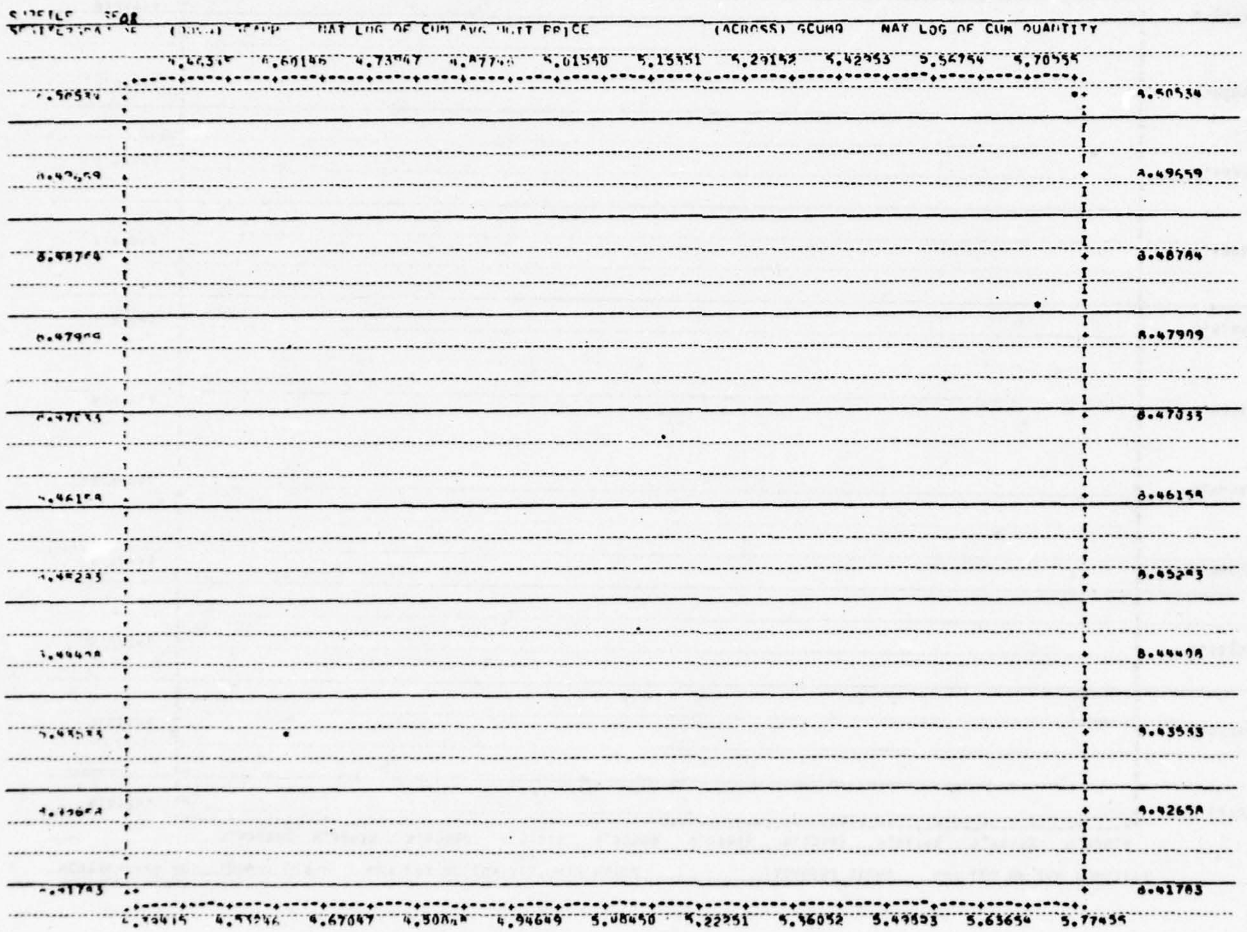


FIGURE A8 - PRICE EXPERIENCE CURVE, SUBFILE 08

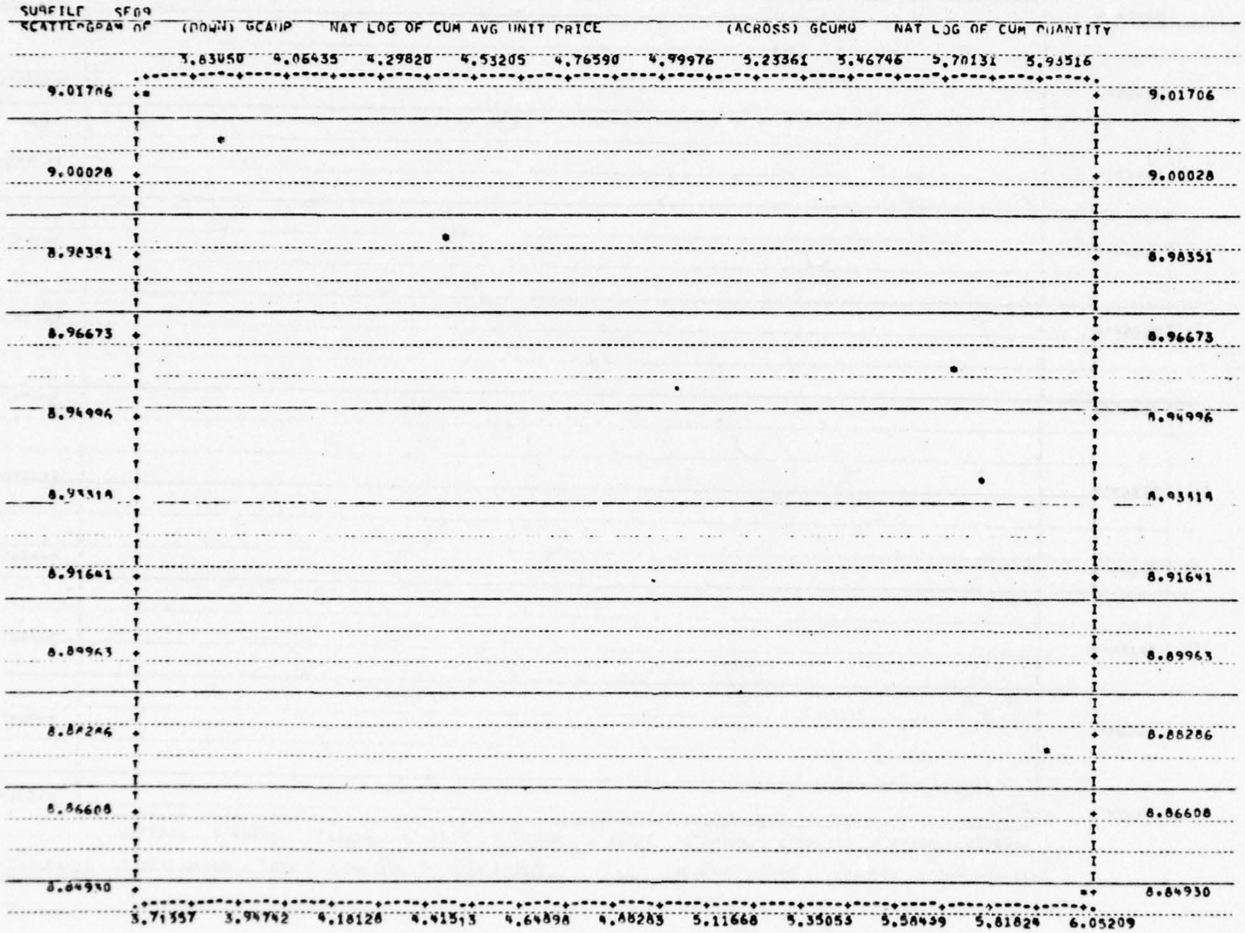


FIGURE A9 - PRICE EXPERIENCE CURVE, SUBFILE 09

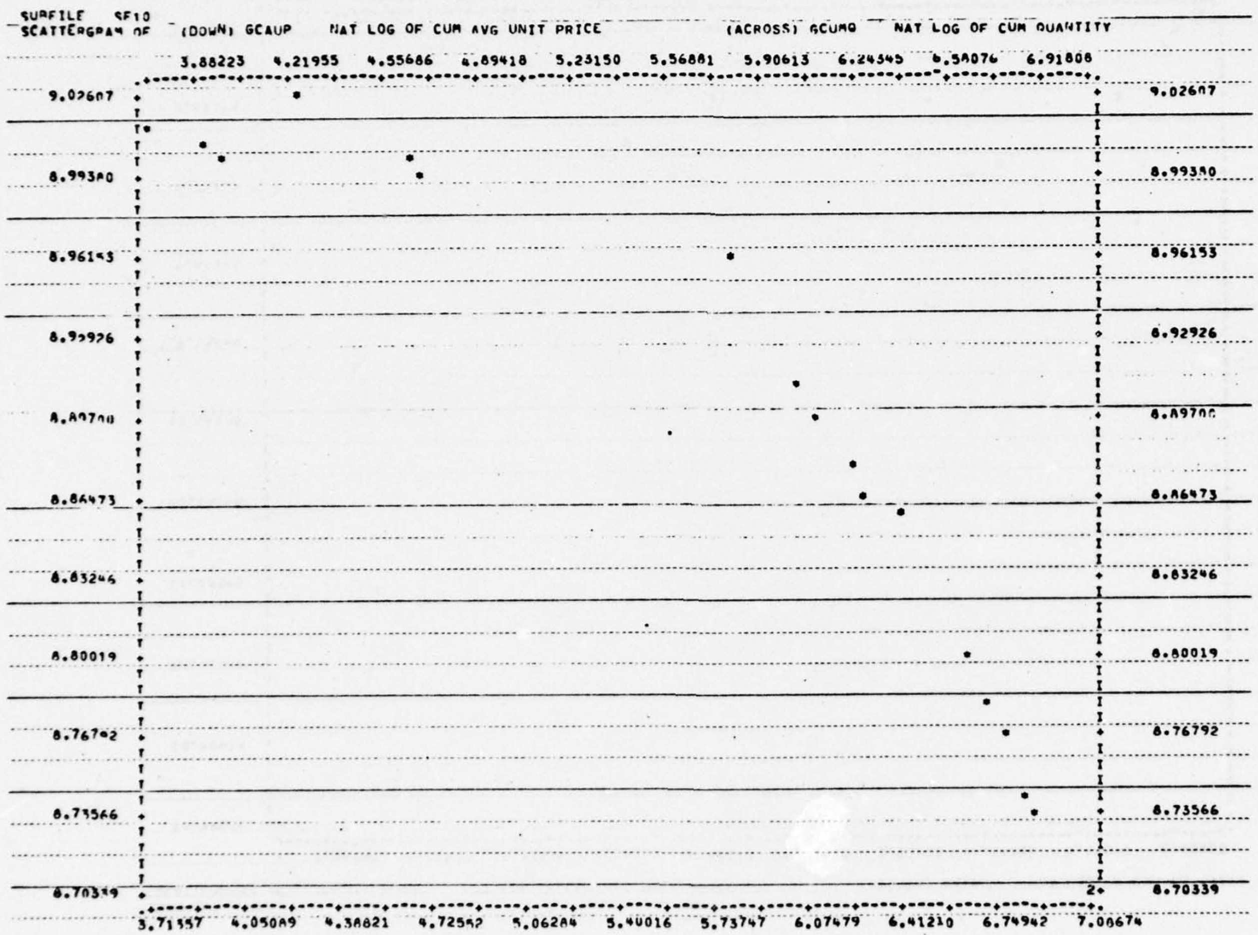


FIGURE A10 - PRICE EXPERIENCE CURVE, SUBFILE 10

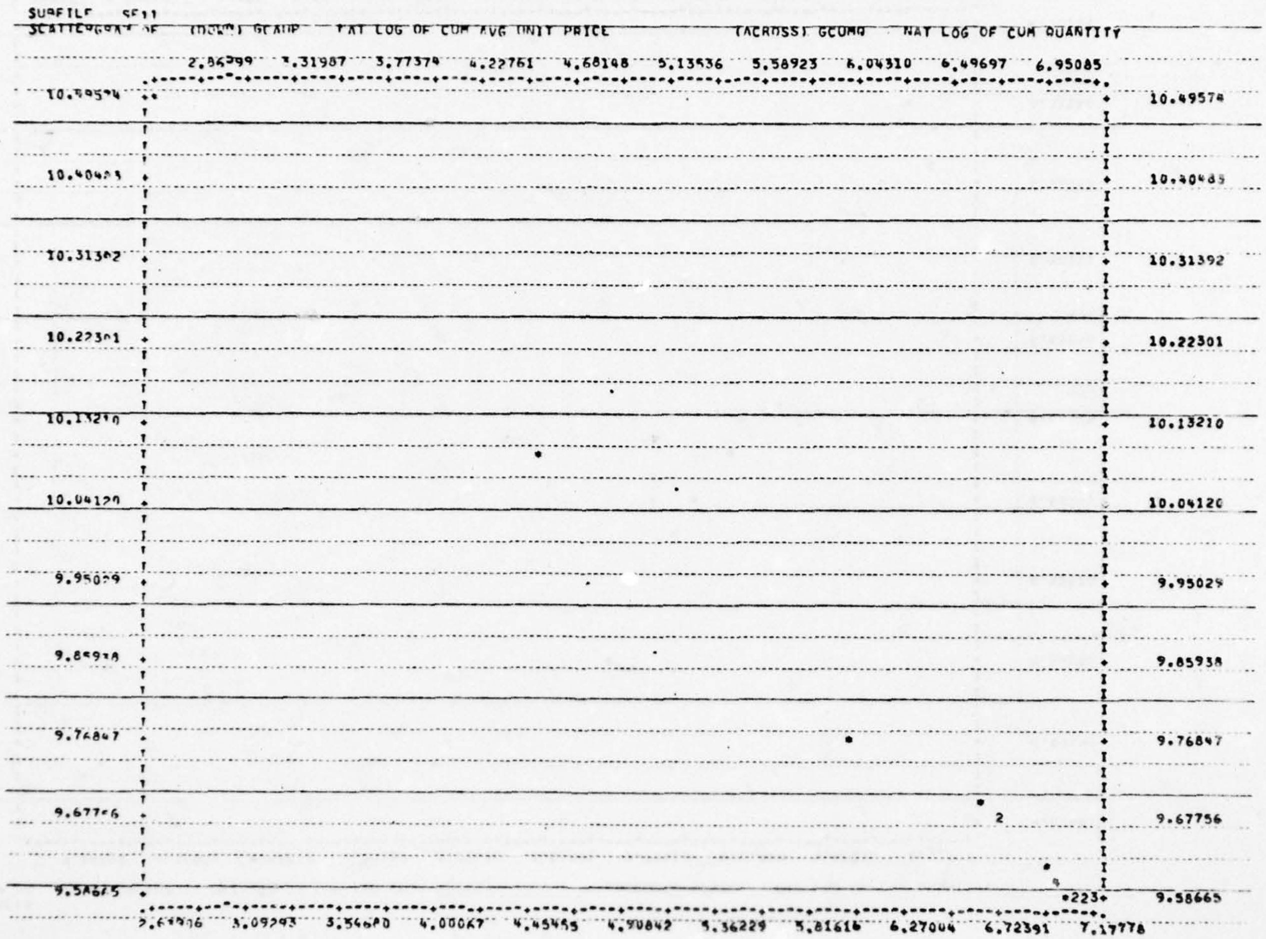


FIGURE A11 - PRICE EXPERIENCE CURVE, SUBFILE 11

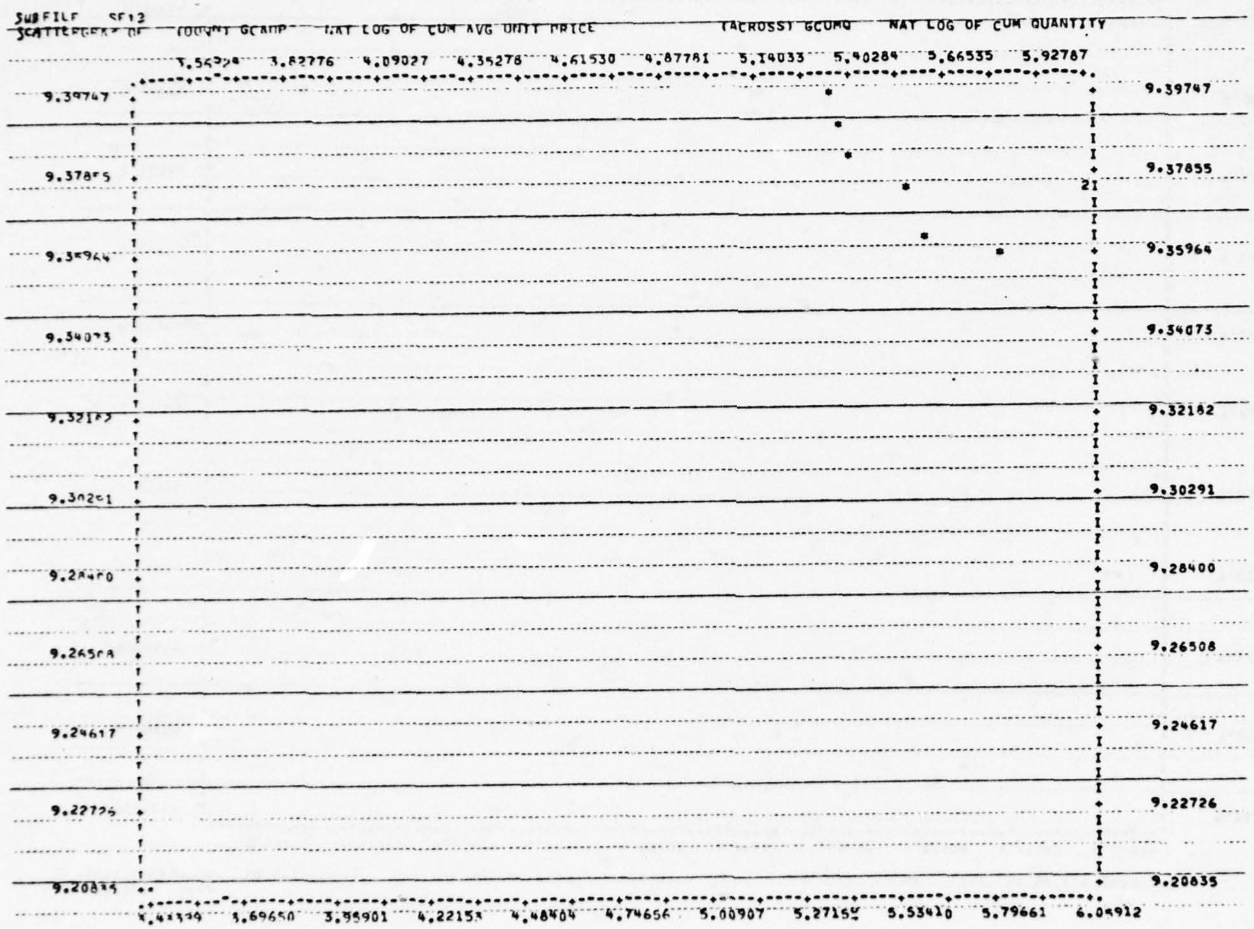


FIGURE A12 - PRICE EXPERIENCE CURVE, SUBFILE 12

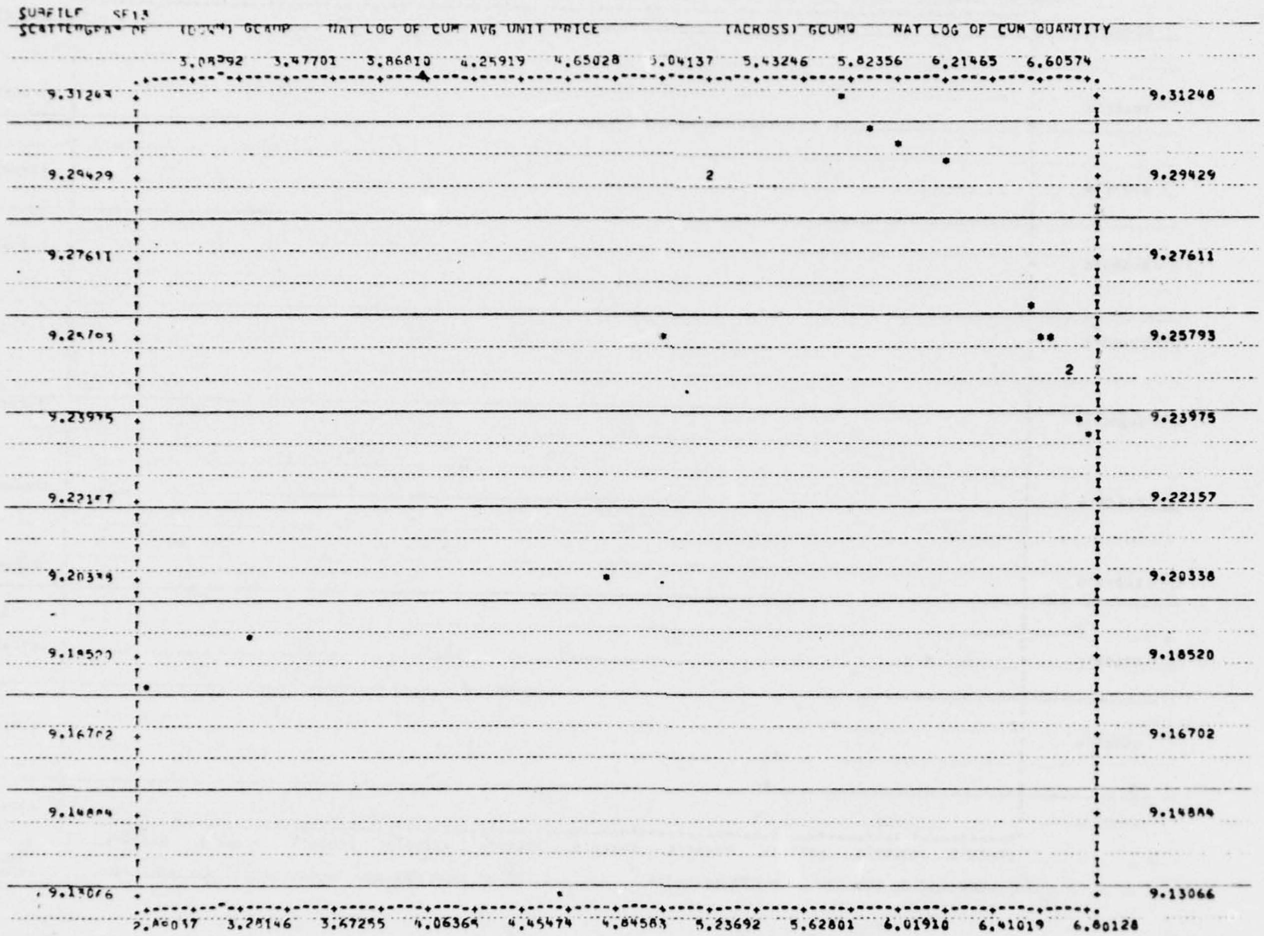


FIGURE A13 - PRICE EXPERIENCE CURVE, SUBFILE 13

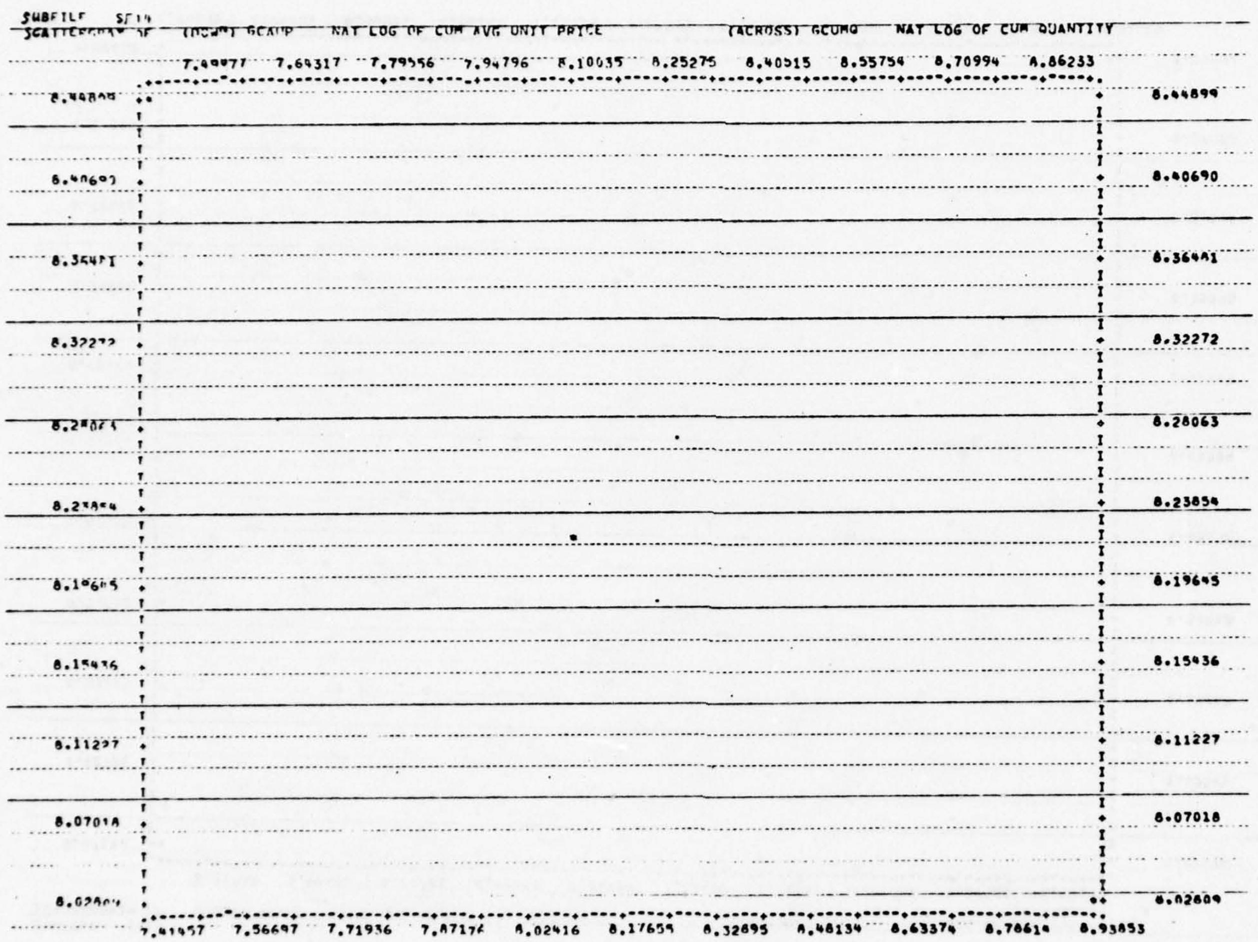


FIGURE A14 - PRICE EXPERIENCE CURVE, SUBFILE 14

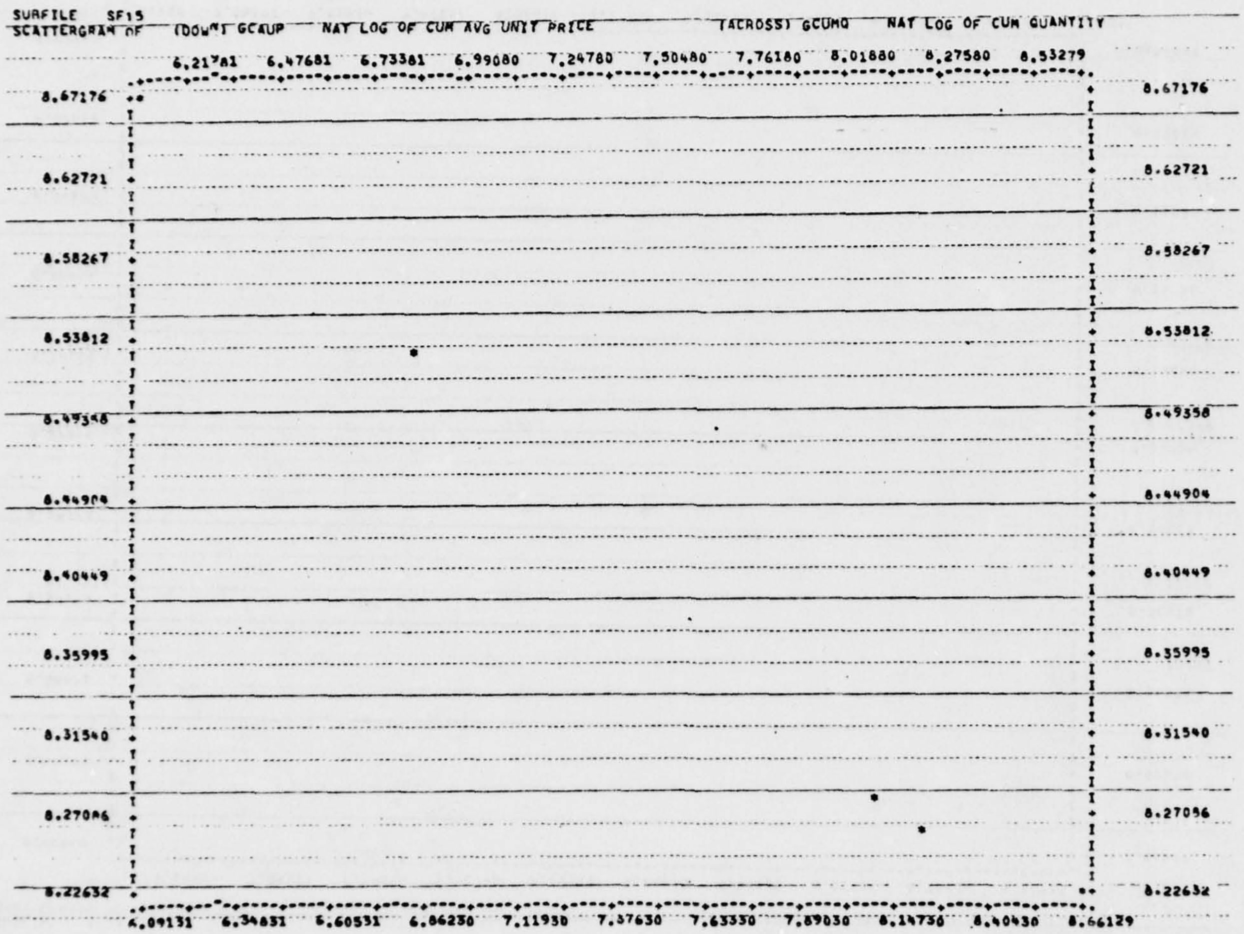


FIGURE A15 - PRICE EXPERIENCE CURVE, SUBFILE 15

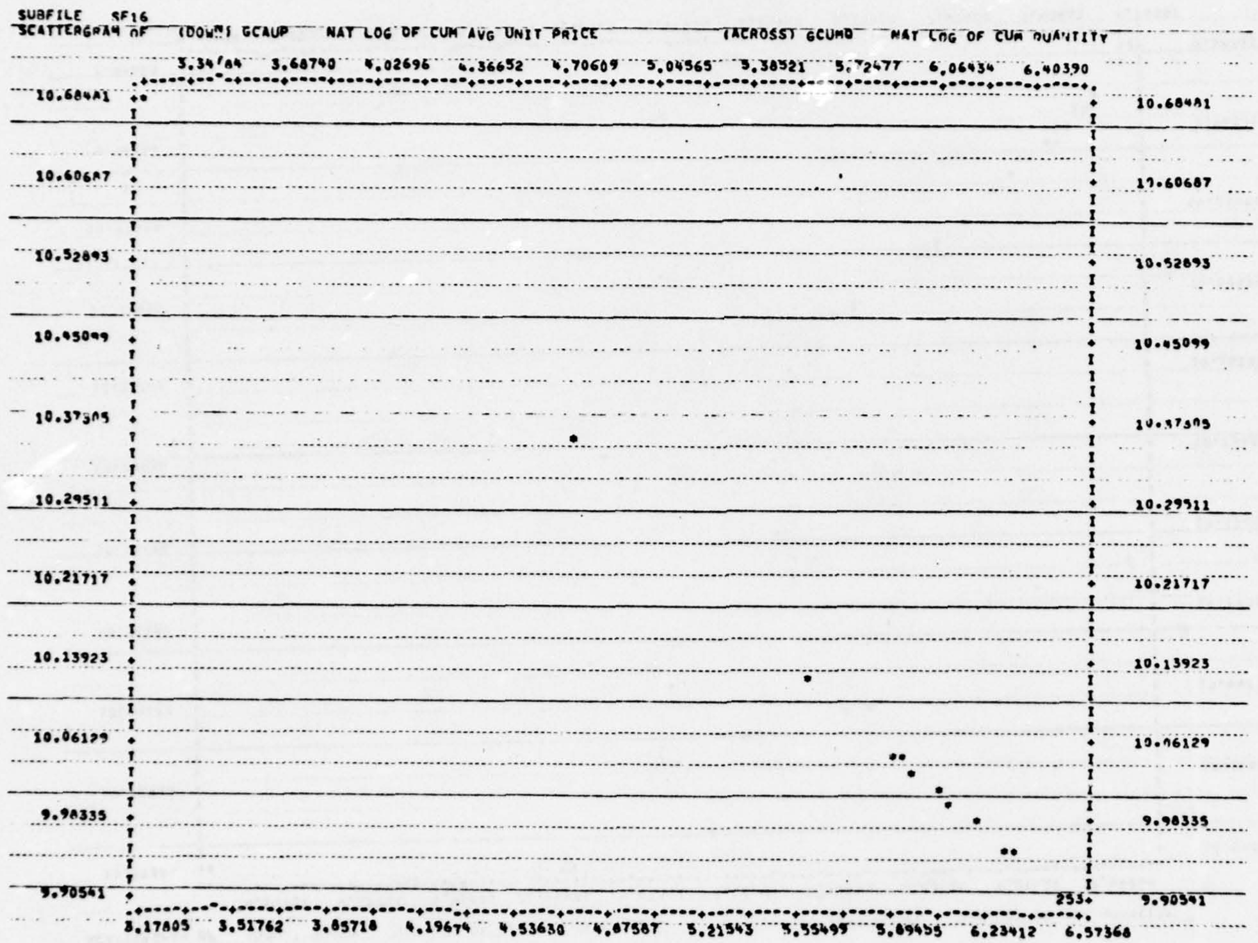


FIGURE A16 - PRICE EXPERIENCE CURVE, SUBFILE 16

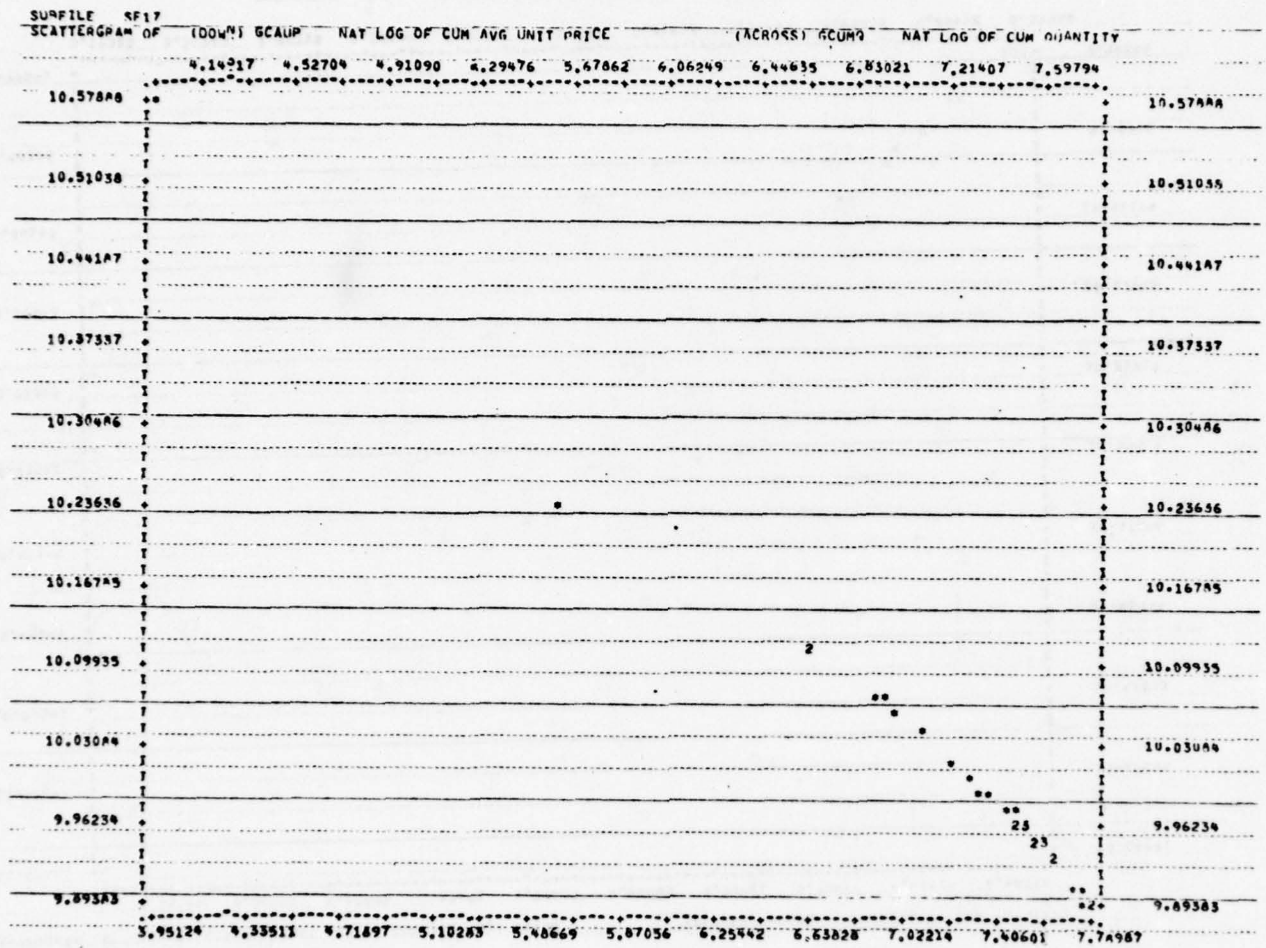


FIGURE A17 - PRICE EXPERIENCE CURVE, SUBFILE 17

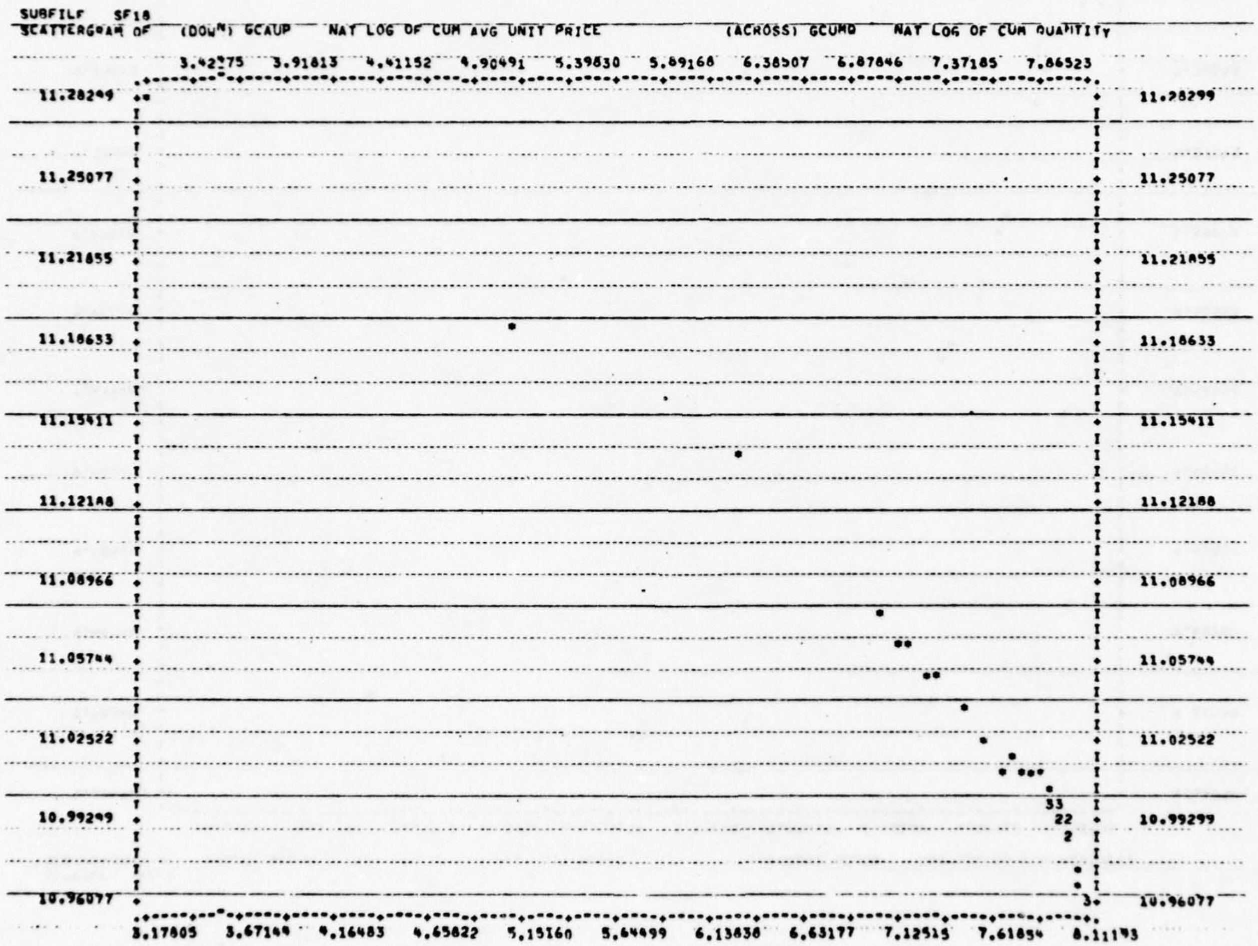


FIGURE A18 - PRICE EXPERIENCE CURVE, SUBFILE 18

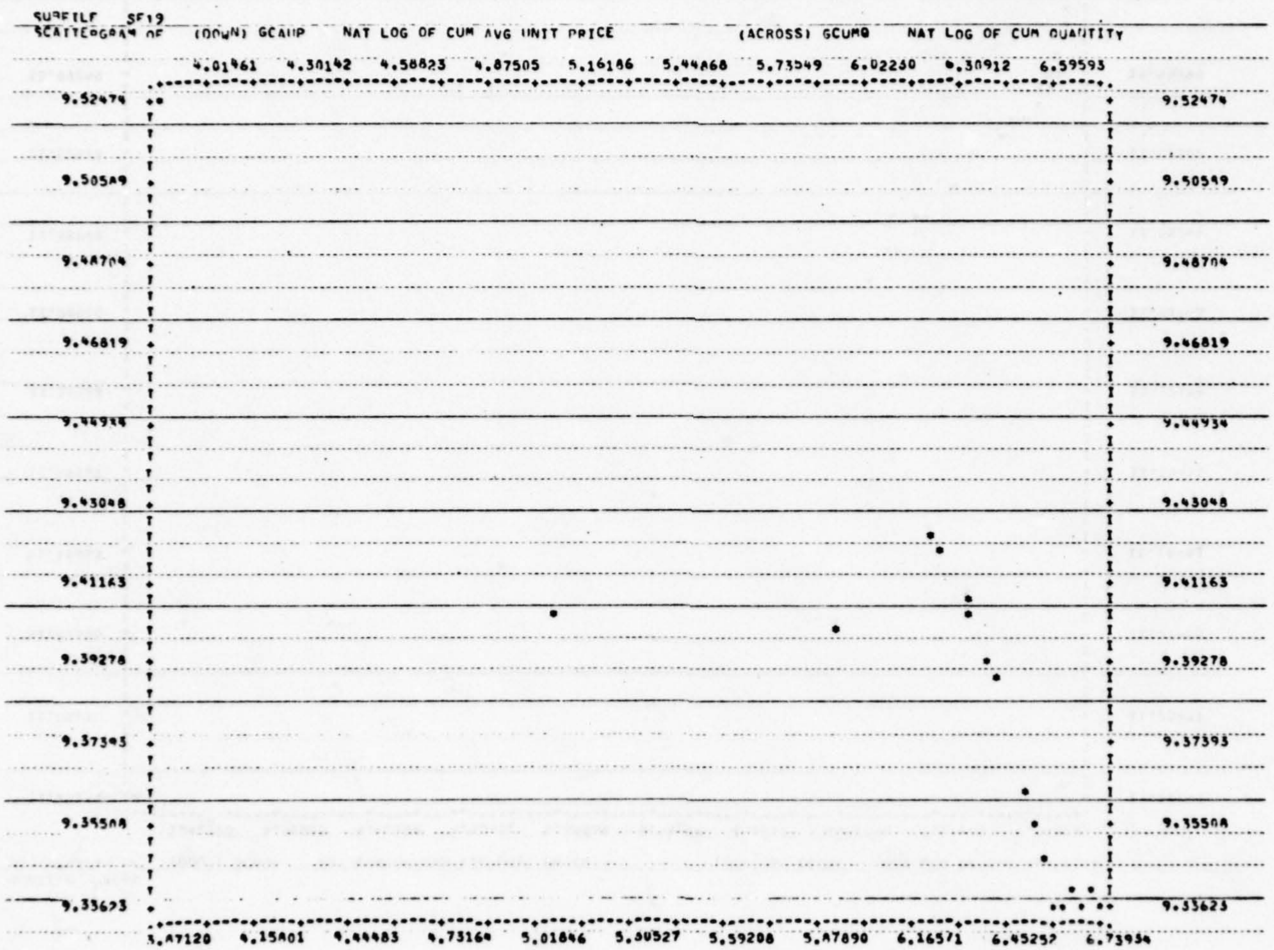


FIGURE A19 - PRICE EXPERIENCE CURVE, SUBFILE 19

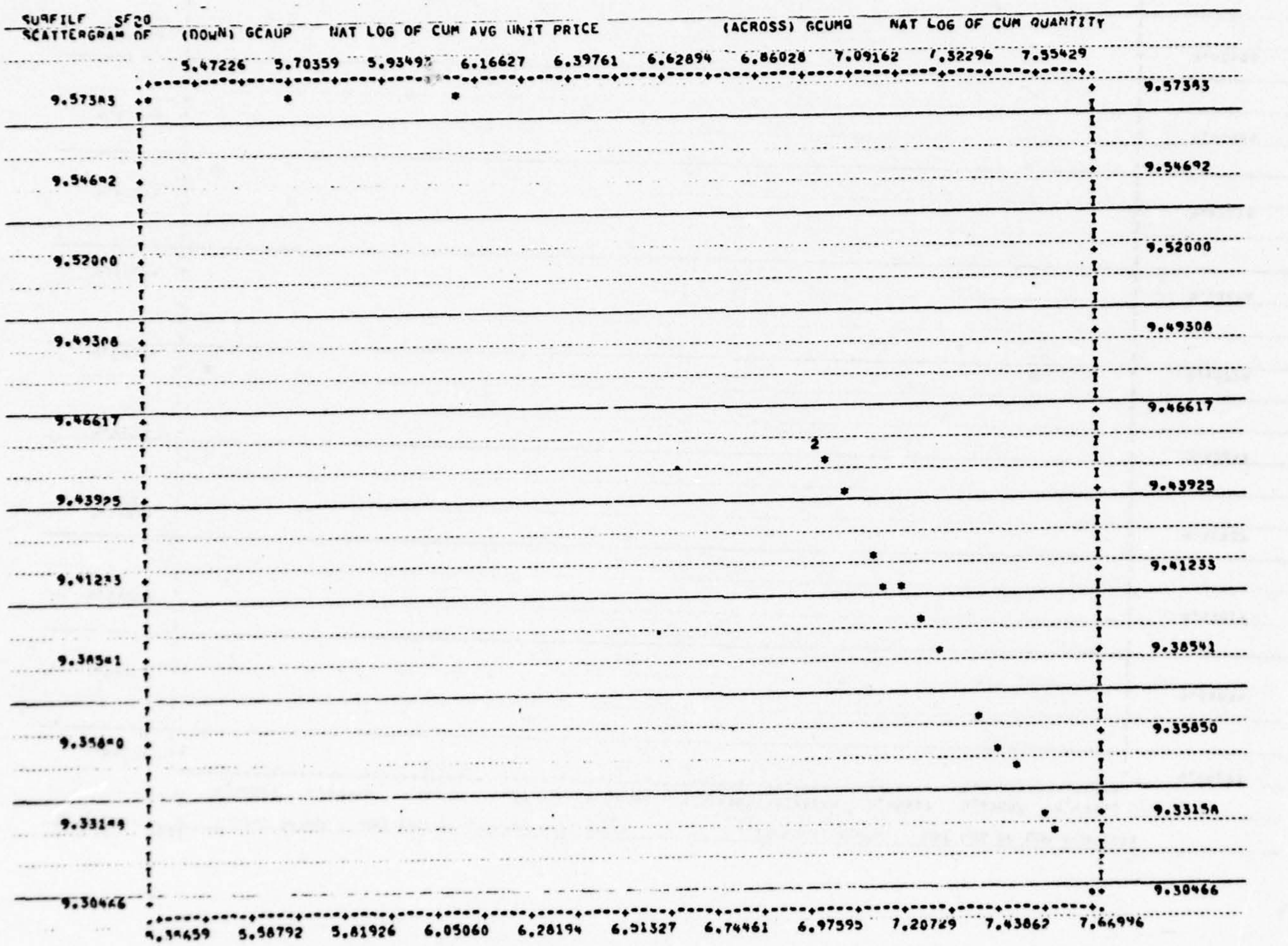


FIGURE A20 - PRICE EXPERIENCE CURVE, SUBFILE 20

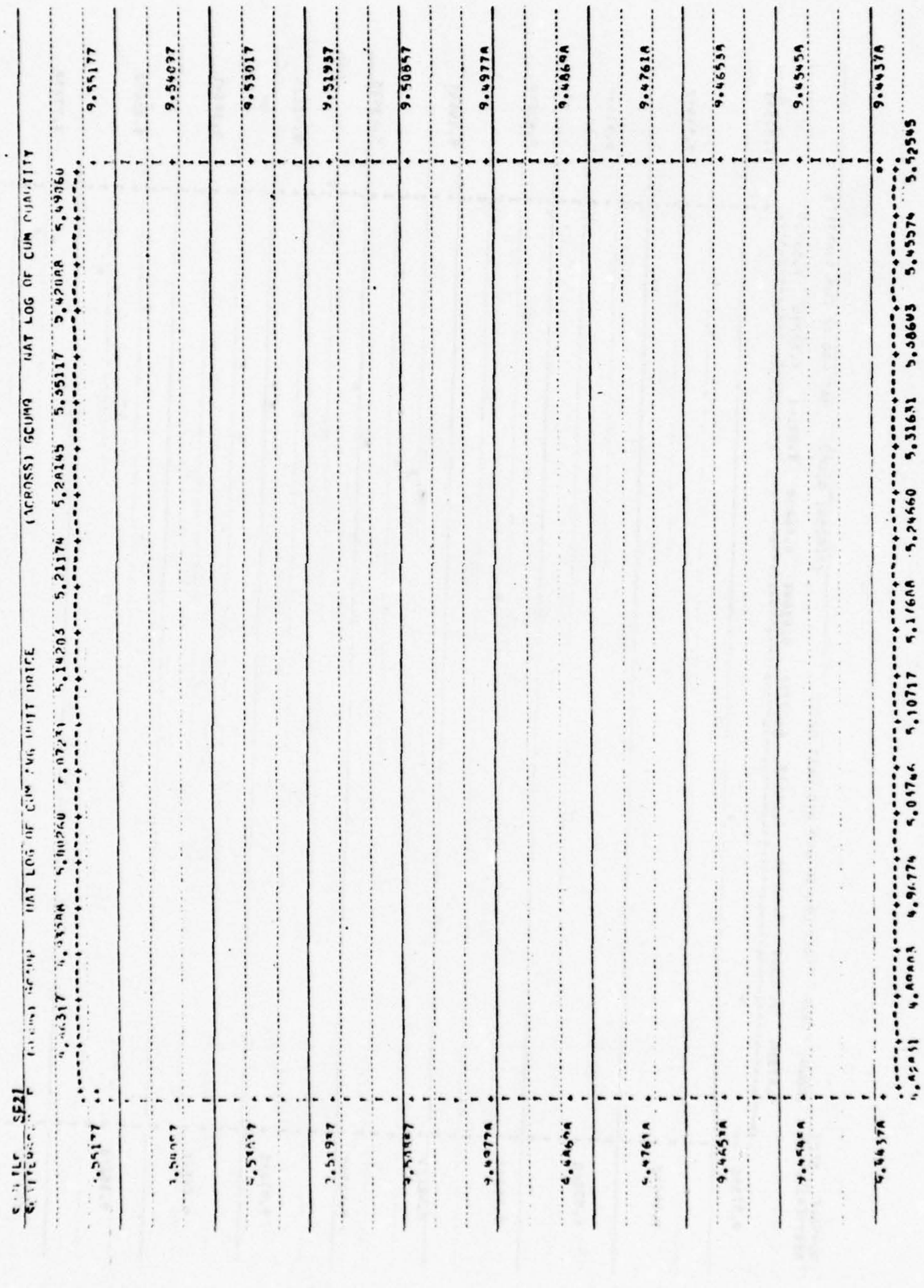


FIGURE A21 - PRICE EXPERIENCE CURVE, SUBFILE 21

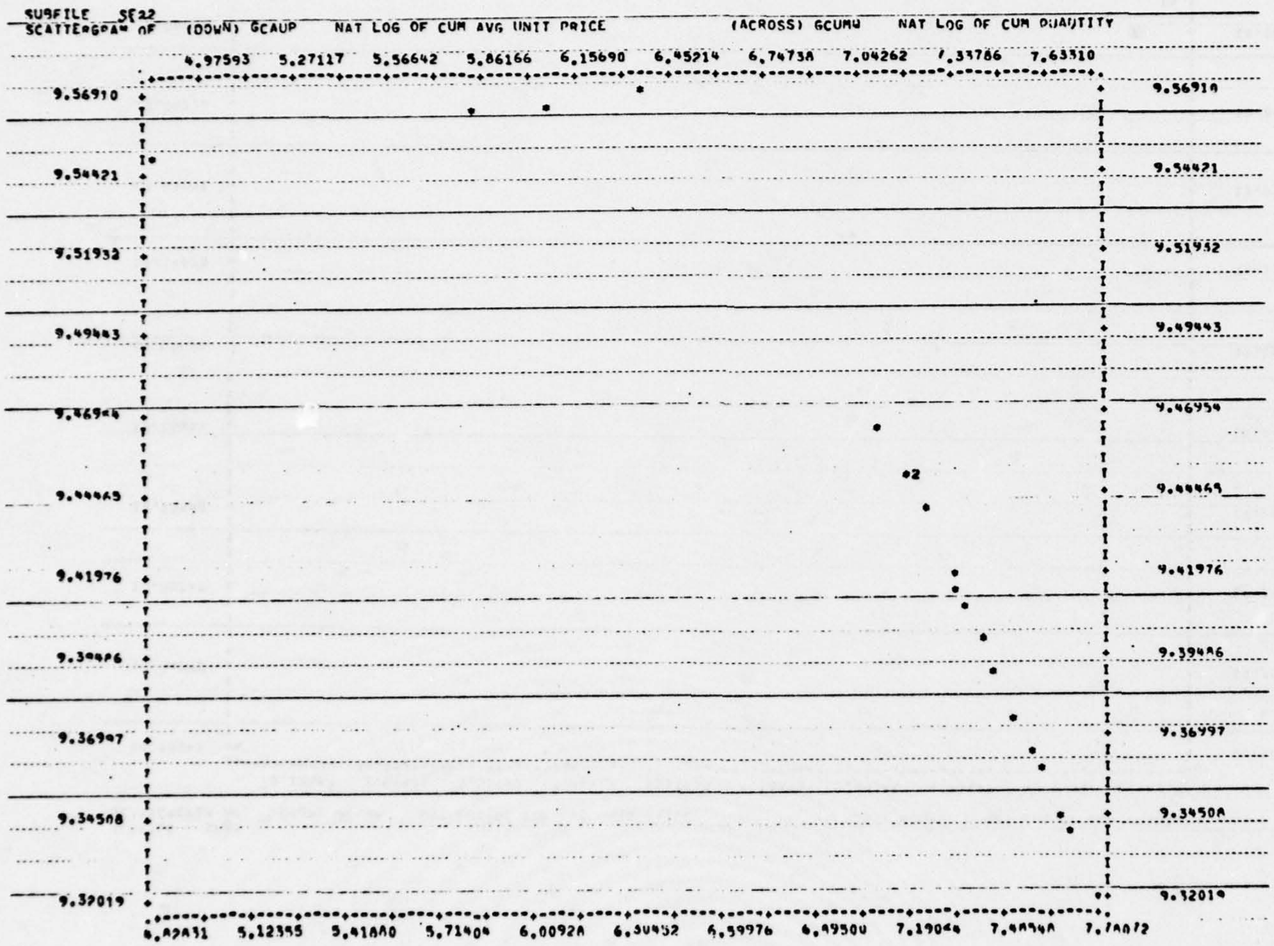


FIGURE A22 - PRICE EXPERIENCE CURVE, SUBFILE 22

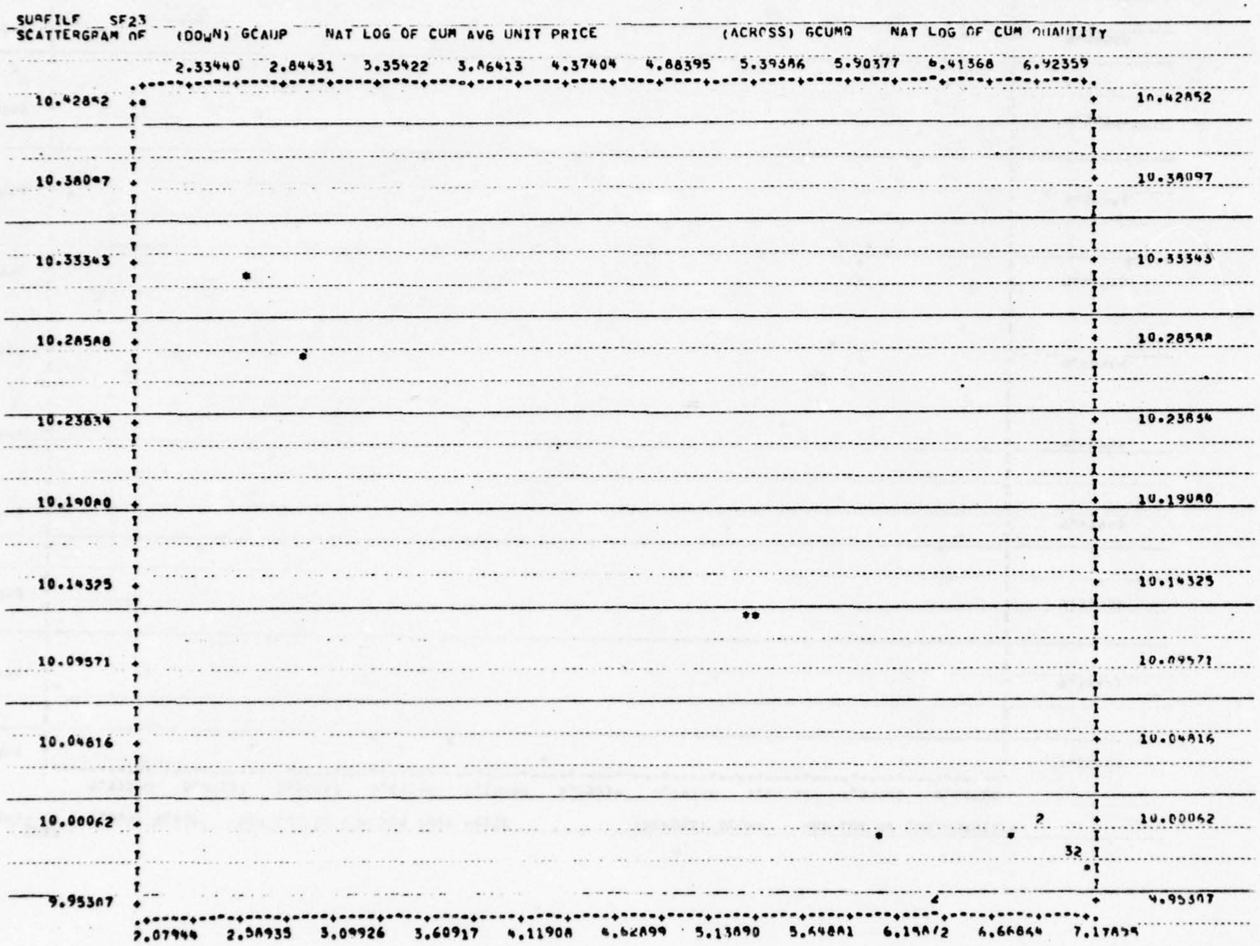


FIGURE A23 - PRICE EXPERIENCE CURVE, SUBFILE 23

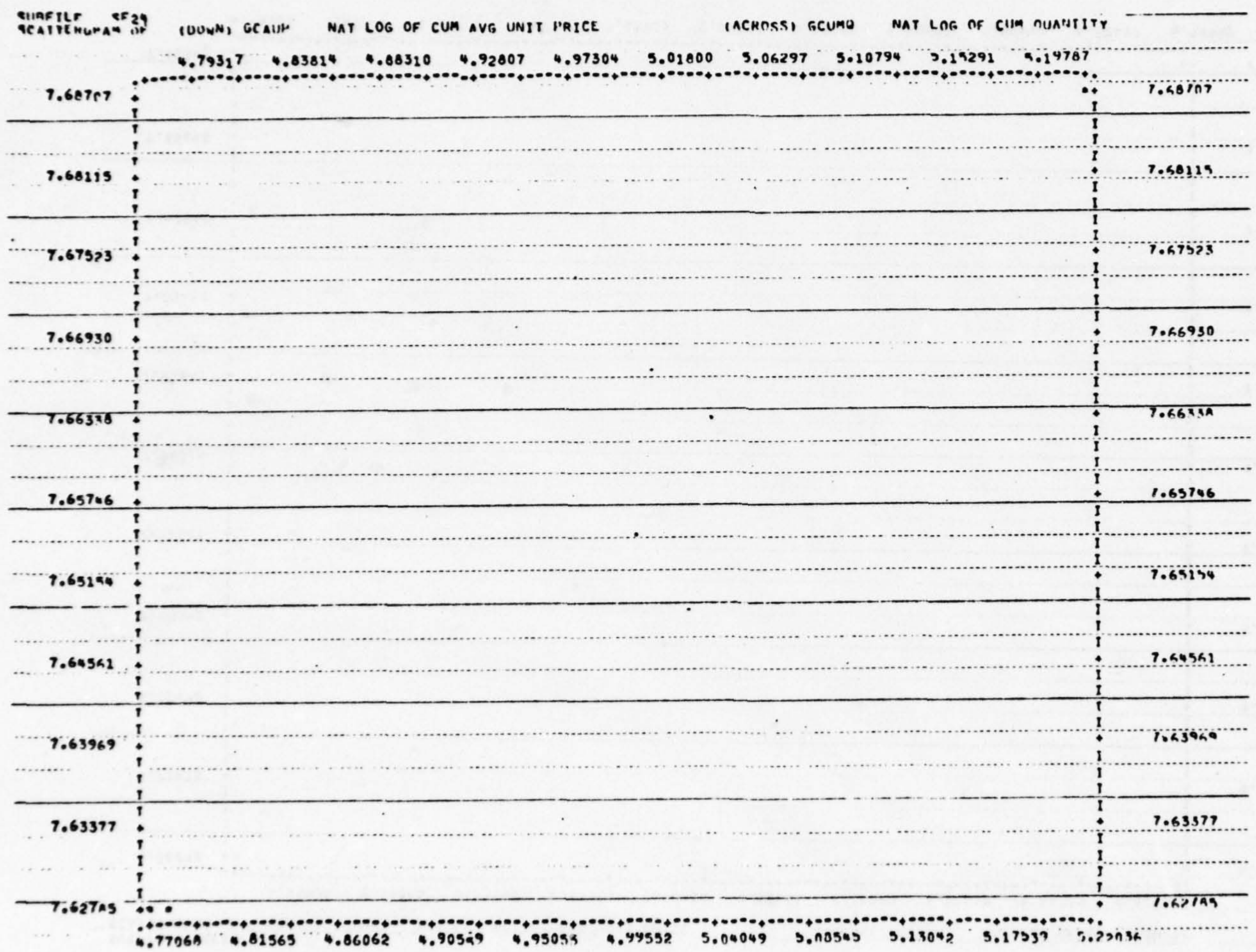


FIGURE A24 - PRICE EXPERIENCE CURVE, SUBFILE 24

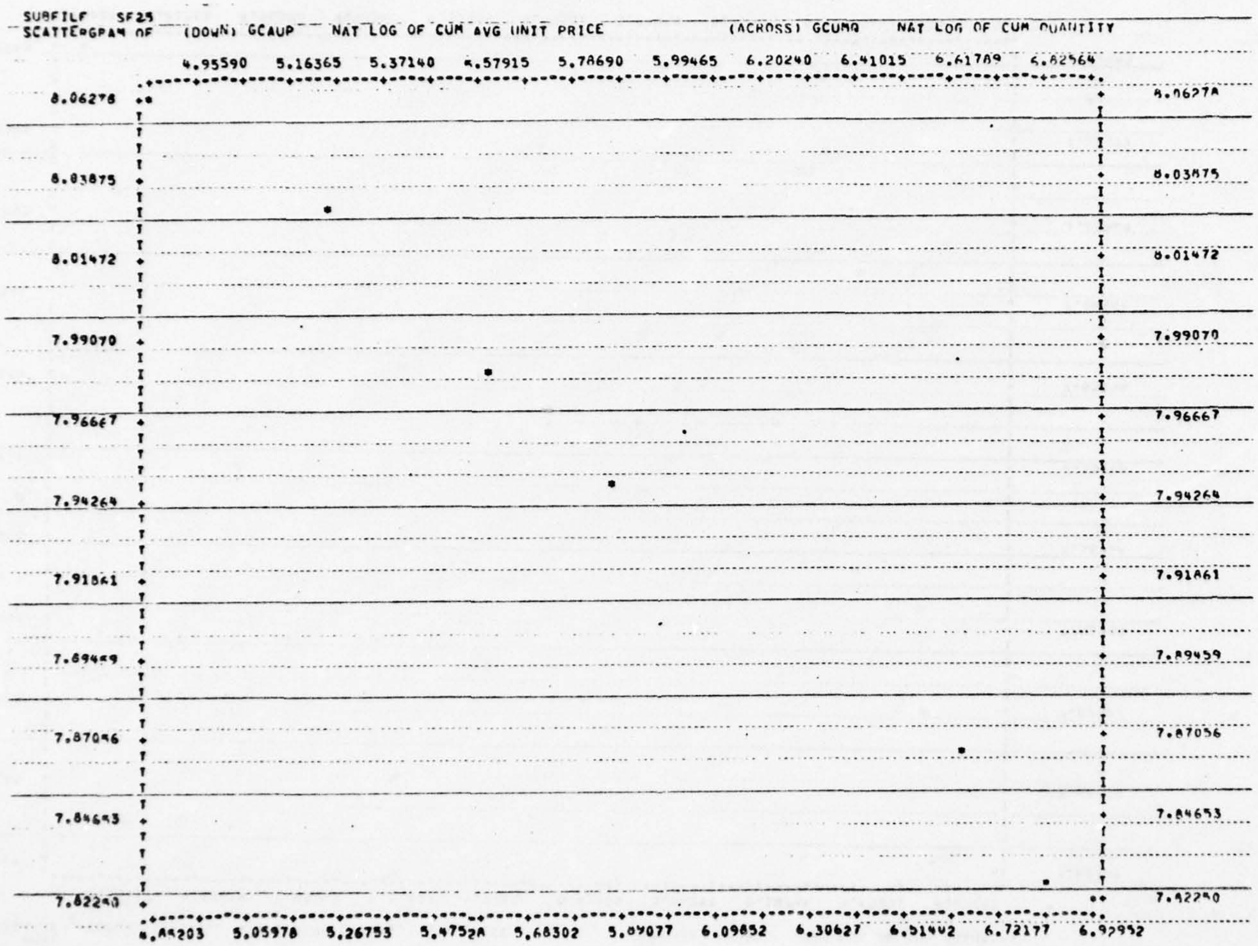


FIGURE A25 - PRICE EXPERIENCE CURVE, SUBFILE 25

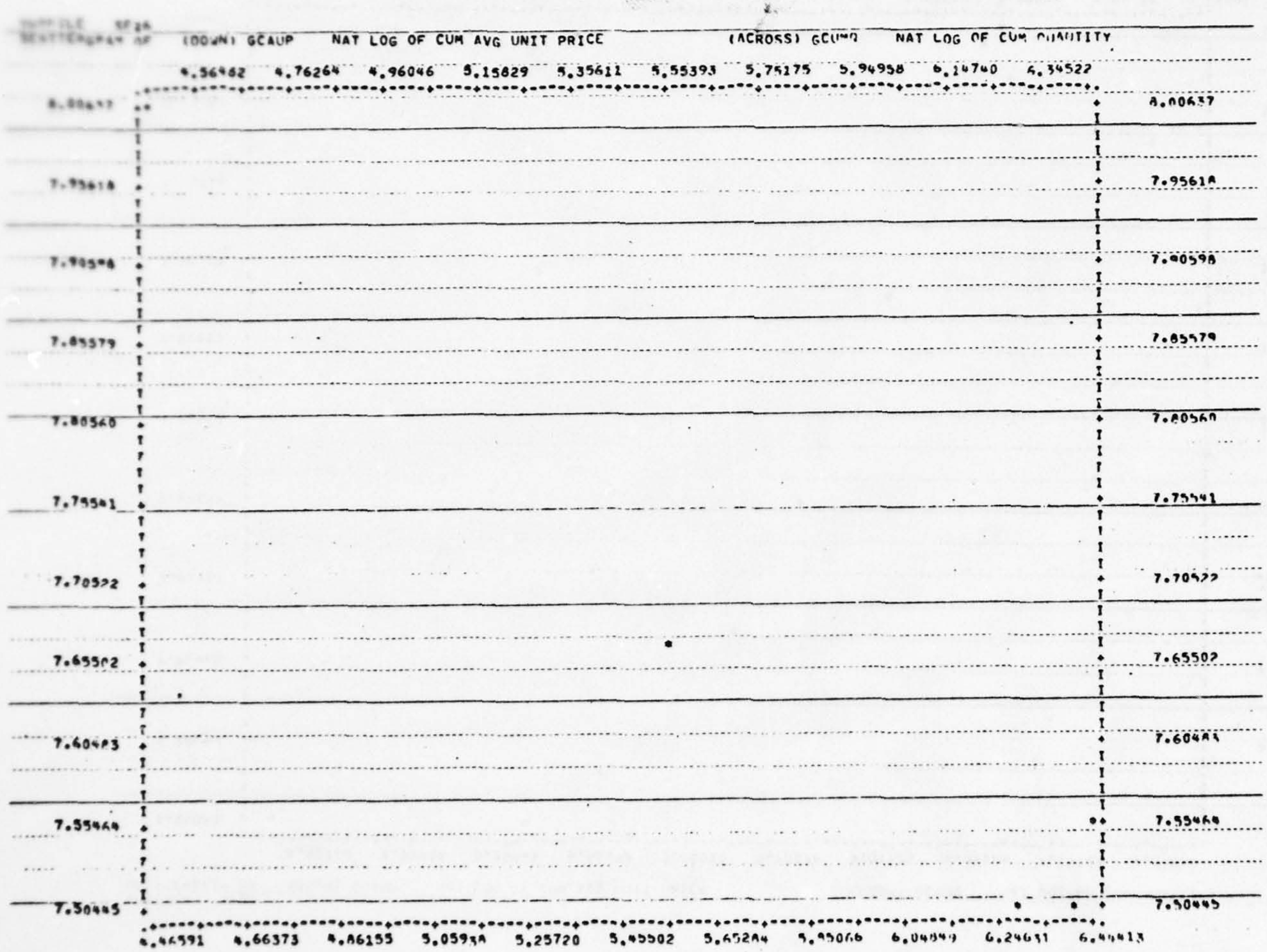


FIGURE A26 - PRICE EXPERIENCE CURVE, SUBFILE 26

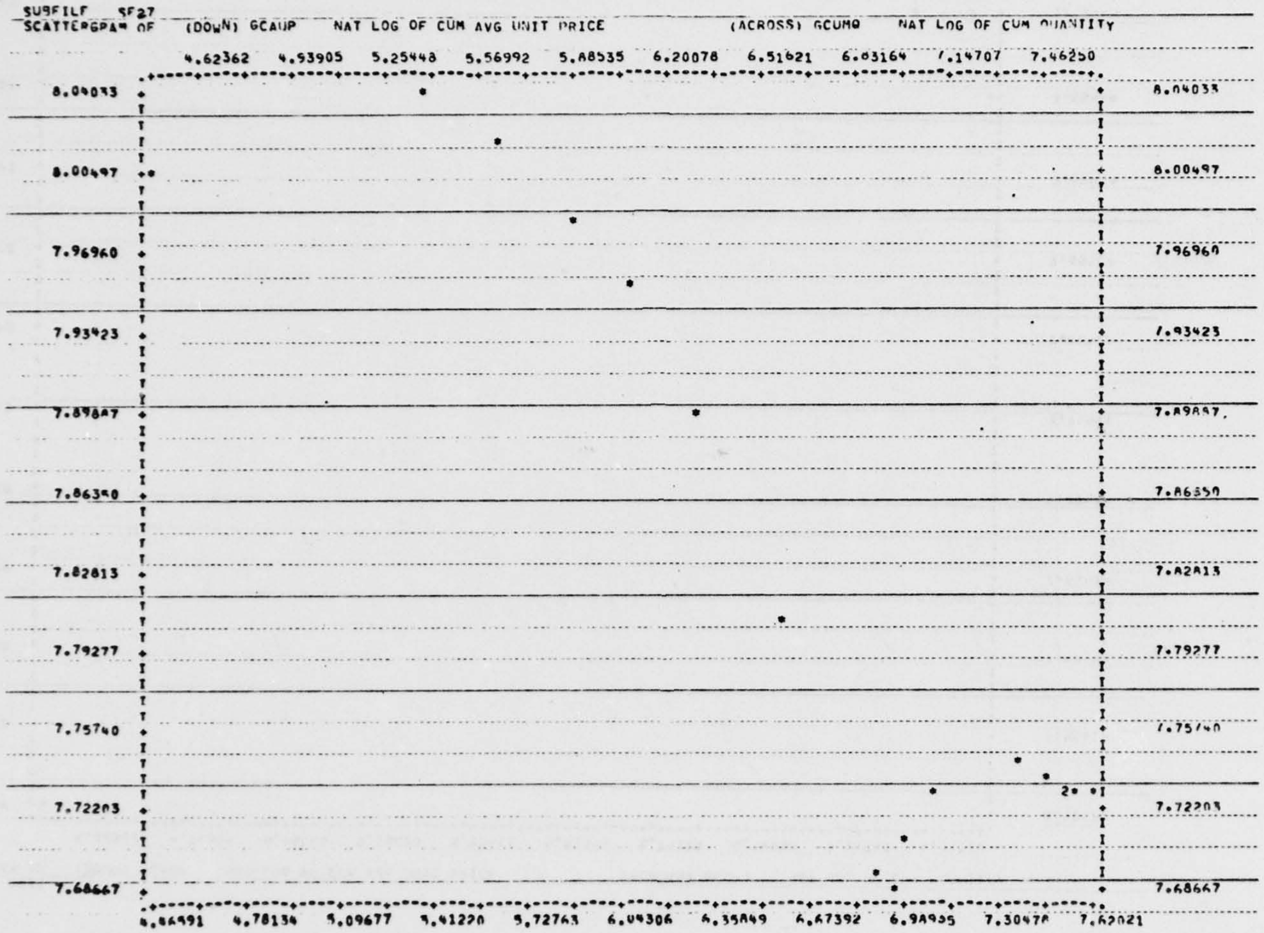


FIGURE A27 - PRICE EXPERIENCE CURVE, SUBFILE 27

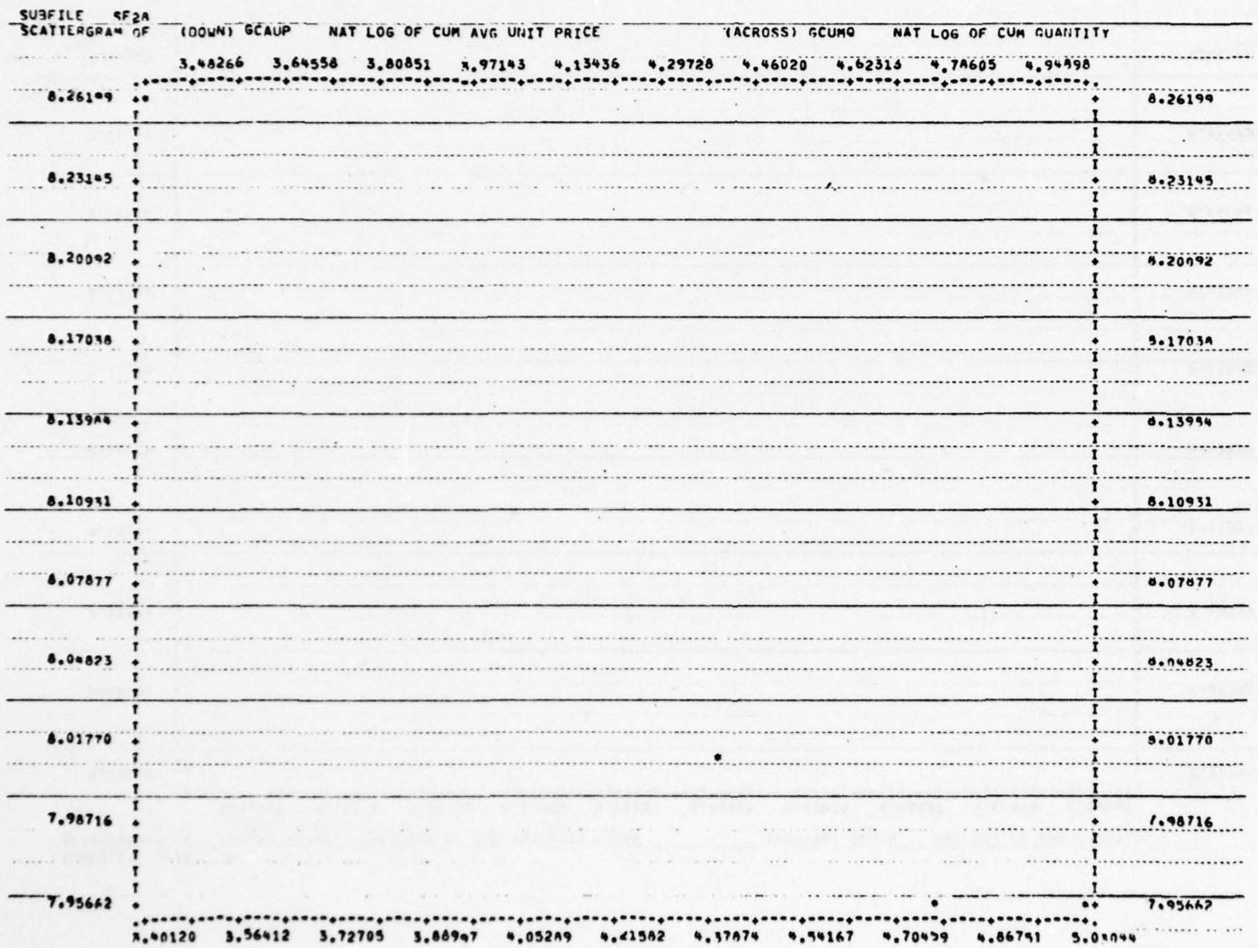


FIGURE A28 - PRICE EXPERIENCE CURVE, SUBFILE 28

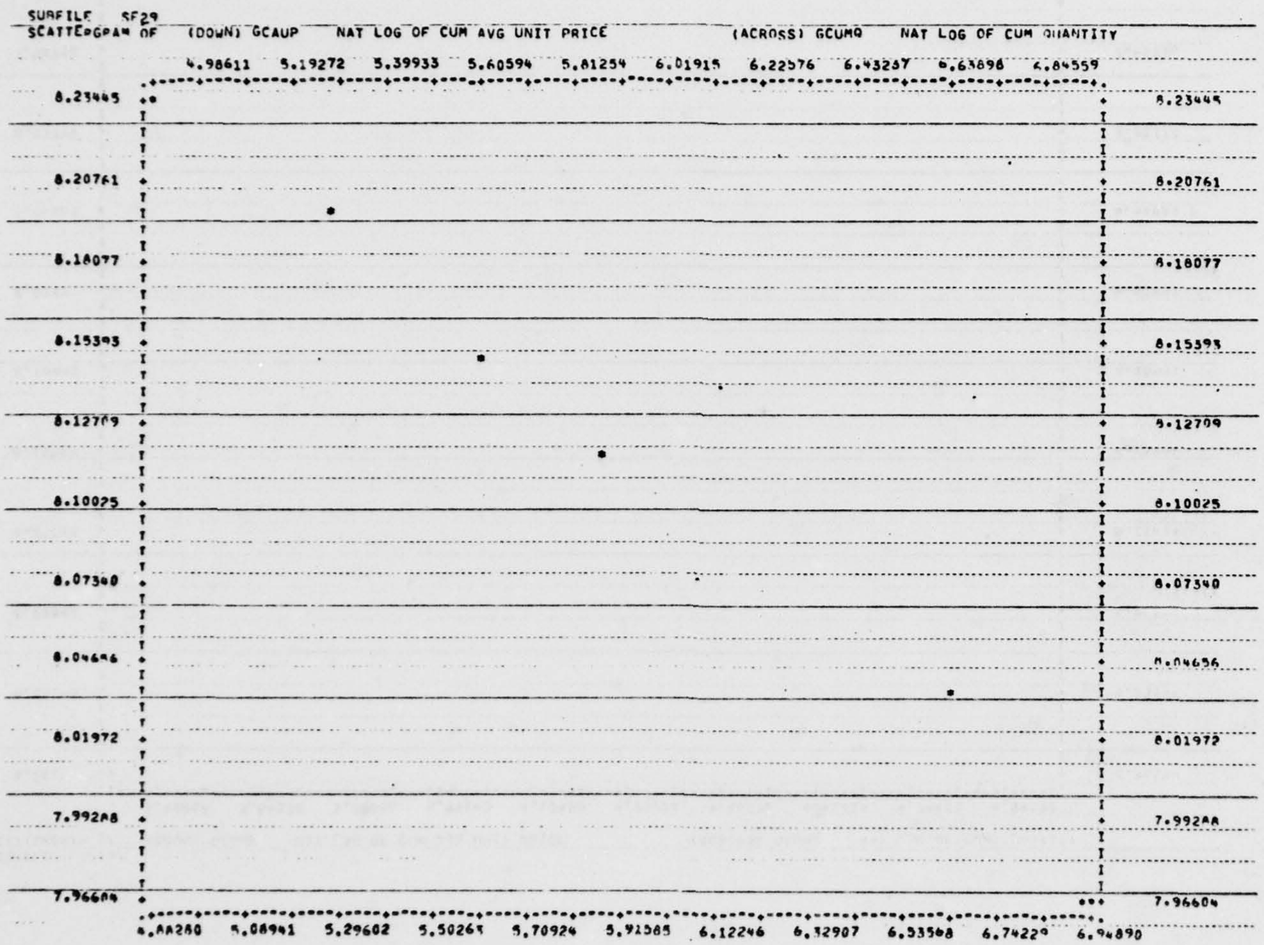


FIGURE A29 - PRICE EXPERIENCE CURVE, SUBFILE 29

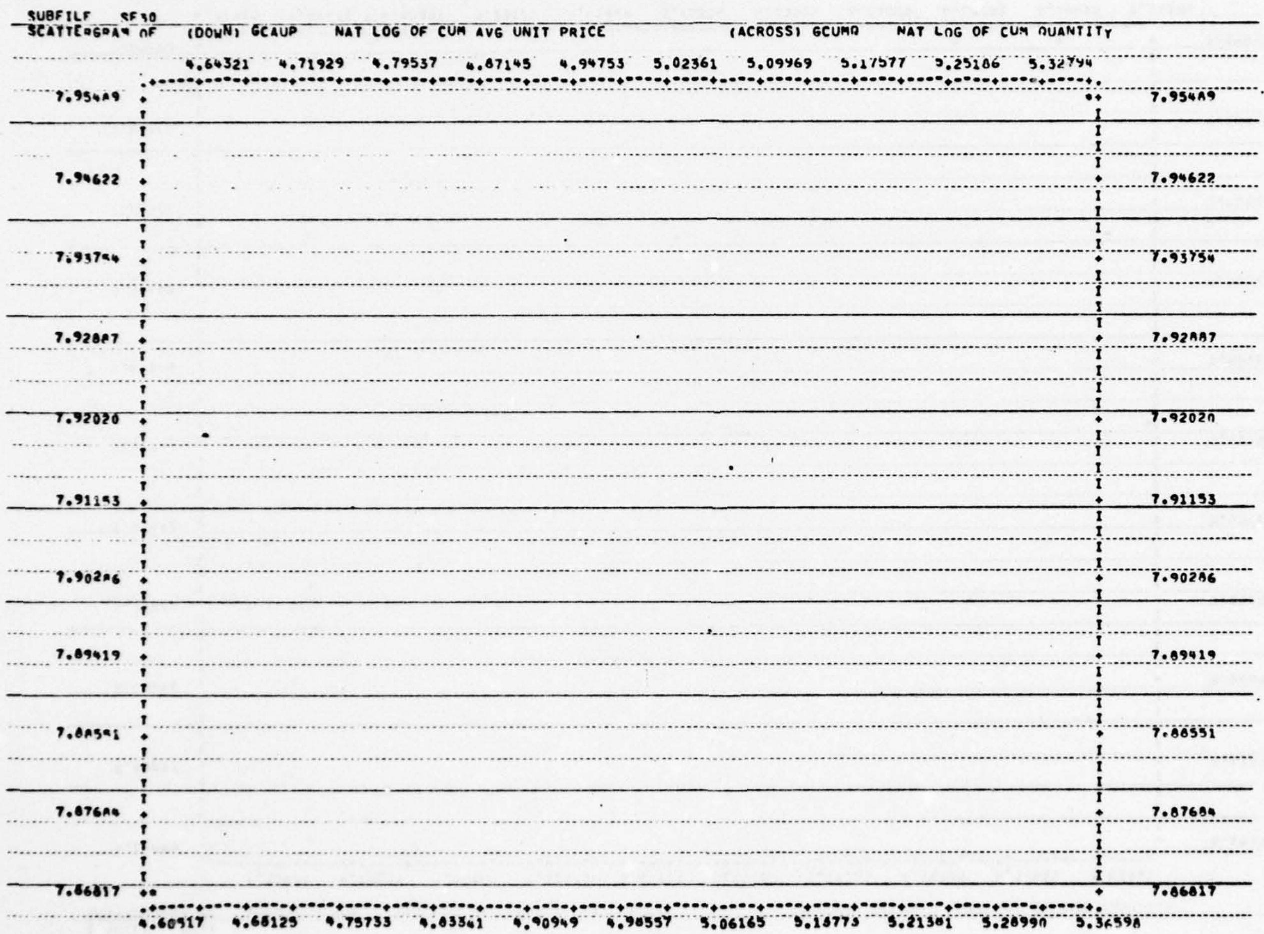


FIGURE A30 - PRICE EXPERIENCE CURVE, SUBFILE 30

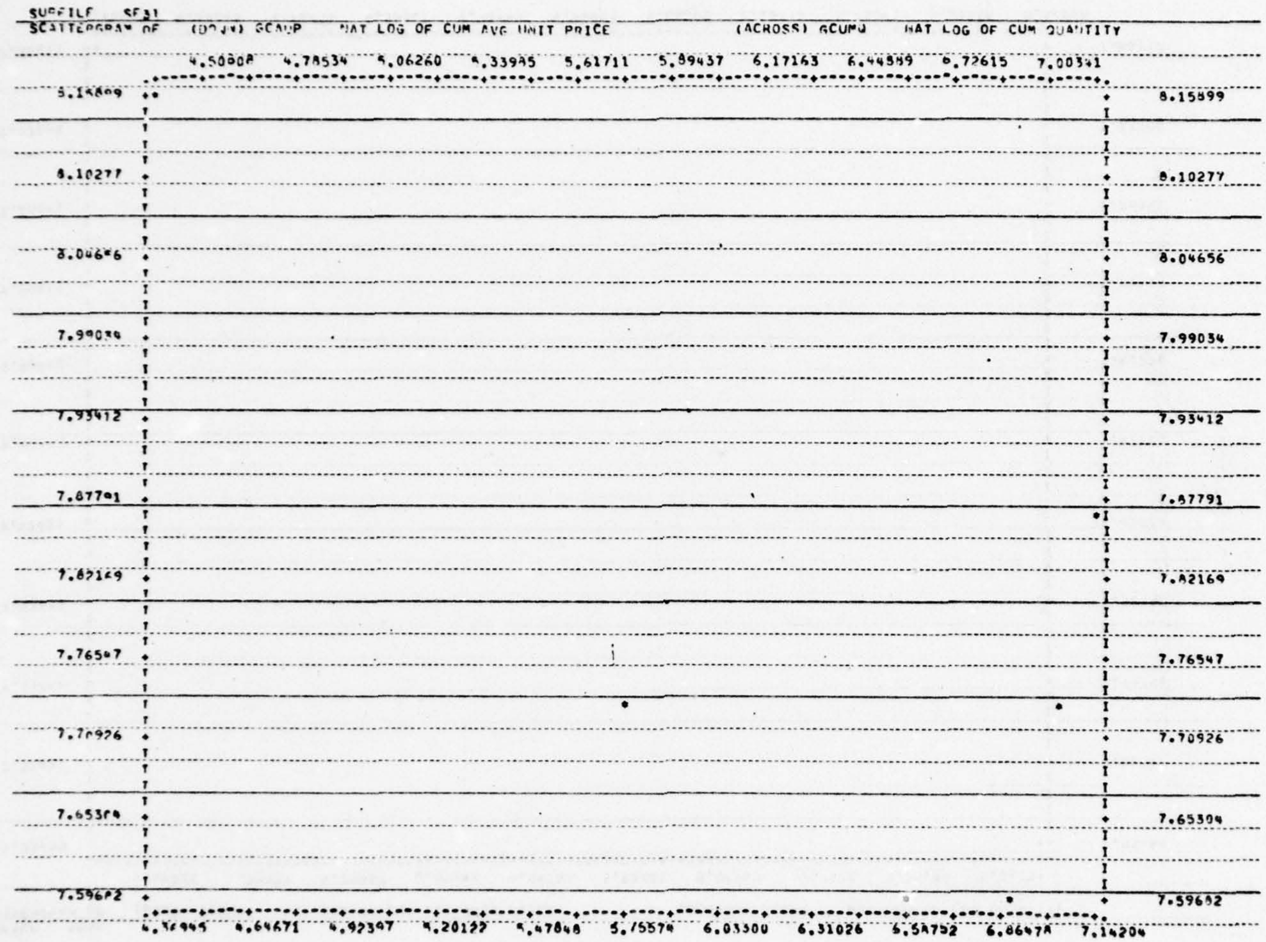


FIGURE A31 - PRICE EXPERIENCE CURVE, SUBFILE 31

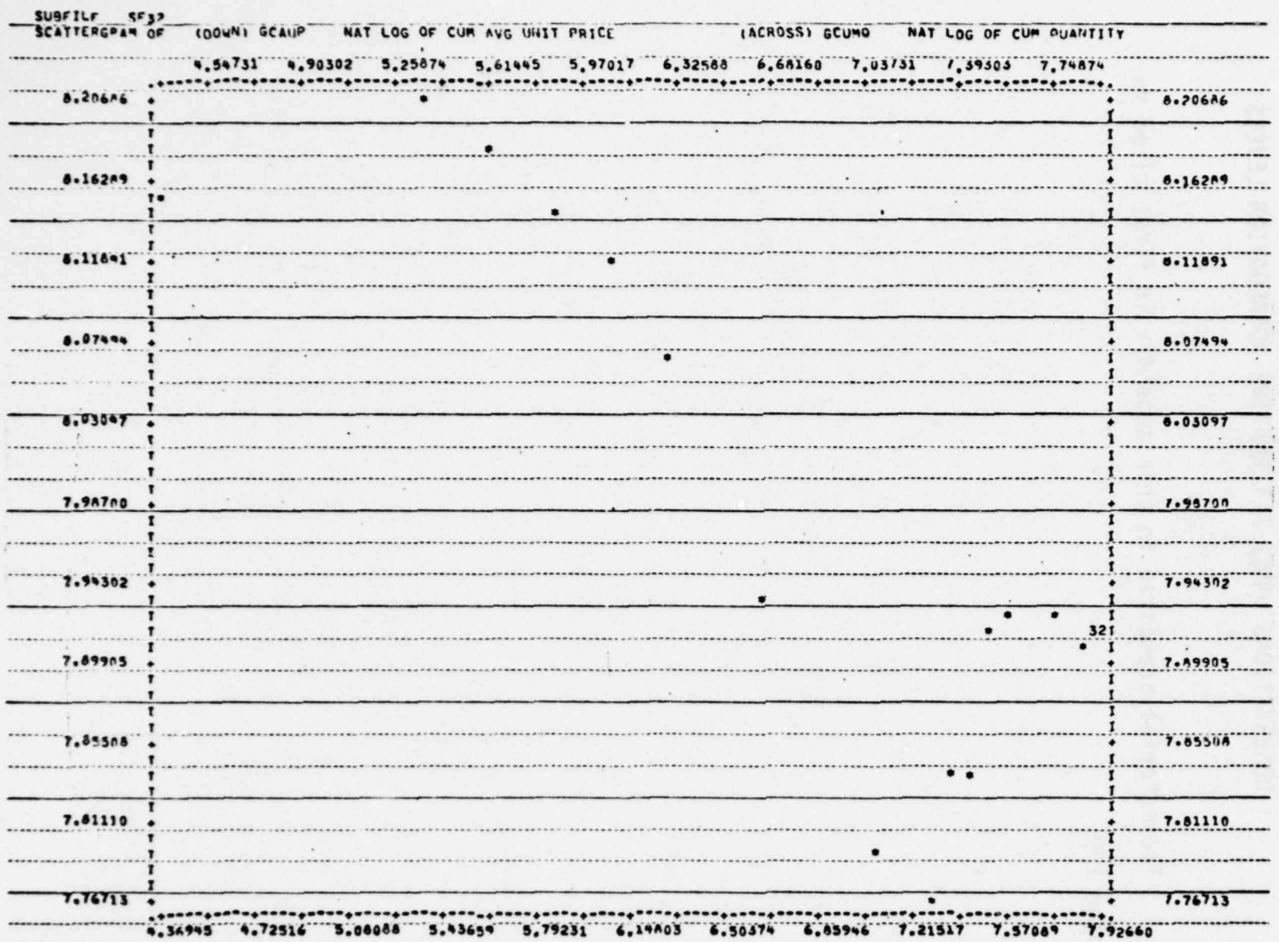


FIGURE A32 - PRICE EXPERIENCE CURVE, SUBFILE 32

APPENDIX D

OBSERVATIONS UNDER ALTERNATIVE AGGREGATION LEVELS

The material presented in this appendix is first cited on page 139.

TABLE A3 - OBSERVED REGRESSION SLOPES

Subfile	Direct Labor	Purchased Material	Total Mfg	Price
		Aggregation Level		
		CUMULATIVE AVERAGE THEORY		
01	.84600	.96699	.91523	.90473
02	.77548	.90454	.87845	.83080
03	.75969	.86026	.81408	.92951
04	.86060	.86491	.86841	.85446
05	.80170	.84196	.81732	1.05445
06	.96812	.95391	.83406	.84933
11	.94875	.95695	.87736	.87115
12	1.00320	1.00716	1.03374	1.04564
13	.85874	.85275	.84710	1.01590
14	.93850	.92514	.81599	.82657
15	.96433	.95361	.86833	.88216
16	.76140	.84958	.83331	.85019
17	.85827	.93855	.91265	.88837
18	.84104	.99120	.90394	.95525
		UNIT THEORY		
01	.49503	.83325	.73459	.87438
02	.55354	.74454	.69969	.82183
03	.48608	.93349	.77668	.92702
04	.81275	.83662	.83954	.82840
05	.76068	.84930	.81607	1.05923
06	.95128	.93560	.80316	.81504
11	.99203	.88290	.85416	.86684
12	.99508	.95721	.97249	1.02319
13	.80534	.77865	.78768	.98185
14	.92985	.91437	.78504	.79546
15	.96908	.95268	.87780	.88458
16	.45145	.87080	.77505	.85992
17	.63755	.73010	.72413	.86078
18	.59454	.93293	.77475	.92640

TABLE A4 - OBSERVED COEFFICIENTS OF DETERMINATION

	Aggregation Level			
Subfile	Direct Labor	Purchased Material	Total Mfg	Price
		CUMULATIVE AVERAGE THEORY		
01	.90693	.47550	.85249	.97015
02	.95251	.87680	.89663	.99878
03	.94670	.96560	.96620	.90703
04	.96709	.97309	.97531	.98437
05	.99455	.96552	.97863	.92950
06	.80743	.91816	.99842	.99974
11	.45157	.49976	.99430	.99680
12	.01931	.02241	.22789	.77289
13	.93425	.91681	.93098	.28944
14	.98935	.98923	.98414	.99260
15	.96051	.89962	.98615	.99309
16	.90777	.98107	.92562	.99871
17	.90225	.48217	.76491	.99004
18	.96179	.33336	.96683	.95632
		UNIT THEORY		
01	.57377	.37441	.68146	.86561
02	.68092	.72410	.77086	.91277
03	.71689	.02775	.33796	.35565
04	.39871	.46664	.50737	.58936
05	.83757	.71559	.77779	.54803
06	.73961	.86948	.97865	.99906
11	.00244	.44434	.70426	.77014
12	.00379	.31223	.10147	.05184
13	.88662	.83094	.88292	.06663
14	.93073	.92749	.86433	.91885
15	.82811	.75964	.90062	.95215
16	.69118	.04204	.22149	.63727
17	.27454	.35083	.31823	.82021
18	.31136	.09151	.26099	.41492

TABLE A5 - OBSERVED REGRESSION SIGNIFICANCE LEVELS

Subfile	Aggregation Level: Direct Labor	Purchased Material	Total Mfg	Price
		CUMULATIVE AVERAGE THEORY		
01	.00001	.00001	.00001	.00001
02	.00001	.00001	.00001	.00001
03	.00001	.00001	.00001	.00001
04	.00001	.00001	.00001	.00001
05	.00001	.00004	.00001	.00023
06	.14460	.09235	.01265	.00517
11	.00081	.00036	.00001	.00001
12	.36073	.35034	.09688	.00090
13	.00001	.00001	.00001	.01064
14	.03291	.03310	.04019	.02841
15	.00169	.00696	.00035	.00012
16	.00001	.00001	.00001	.00001
17	.00001	.00001	.00001	.00001
18	.00001	.00042	.00001	.00001
		UNIT THEORY		
01	.00001	.00010	.00001	.00001
02	.00026	.00011	.00004	.00001
03	.00001	.19843	.00059	.00020
04	.00062	.00016	.00007	.00001
05	.00192	.00822	.00431	.02854
06	.17046	.11766	.04668	.00975
11	.42047	.00091	.00001	.00001
12	.43751	.05892	.20174	.27788
13	.00001	.00001	.00001	.15052
14	.08477	.08679	.12007	.09195
15	.01598	.02708	.00686	.00225
16	.00001	.20719	.02435	.00001
17	.00177	.00036	.00072	.00001
18	.00068	.05210	.00196	.00003

APPENDIX E

OBSERVATIONS UNDER ALTERNATIVE INFLATION TREATMENTS

The material presented in this appendix is first cited on page 162.

TABLE A6 - REGRESSION SLOPE ANALYSES, FPGS DEFLATORS

Subfile	R^2	Signif	Slope	SEE
01	.97015	.00001	.90473	.02479
02	.99878	.00001	.83080	.00844
03	.90703	.00001	.92951	.03475
04	.98437	.00001	.85446	.02938
05	.92950	.00023	1.05445	.01387
06	.99974	.00517	.84933	.00403
07	.90595	.00048	.96920	.03155
08	.95920	.01031	1.03884	.01006
09	.77212	.00460	.96238	.03361
10 *	.85672	.00001	.93963	.04482
11	.99680	.00001	.87115	.01324
12	.77289	.00090	1.04564	.02943
13	.28944	.01064	1.01590	.04343
14	.99206	.02841	.82657	.02654
15	.99309	.00012	.88216	.01871
16	.99871	.00001	.85019	.00692
17	.99004	.00001	.88837	.01321
18	.95632	.00001	.95525	.01421
19	.73094	.00001	.96047	.02577
20	.90180	.00001	.91821	.02694
21	1.00000	-	.89819	-
22 *	.77800	.00001	.93877	.03760
23	.93582	.00001	.94469	.03790
24	.99977	.00485	1.09644	.00074
25	.99447	.00001	.92111	.00790
26	.95664	.00194	.84458	.05058
27 *	.80129	.00001	.91494	.06054
28	.95732	.01079	.87149	.03660
29	.98864	.00001	.91437	.01259
30	1.00000	-	1.08221	-
31	.53458	.04935	.90476	.16050
32 *	.65373	.00001	.93123	.08029

* Cross-contractor item-industry composite.

TABLE A7 - REGRESSION SLOPE ANALYSES, GNP DEFLATORS

Subfile	R^2	Signif	Slope	SEE
01	.97022	.00001	.91104	.02304
02	.99924	.00001	.83677	.00639
03	.88345	.00001	.93542	.03601
04	.98624	.00001	.85449	.02753
05	.94277	.00014	1.06862	.01553
06	.99972	.00529	.85445	.00397
07	.89842	.00058	.96839	.03380
08	.97404	.00653	1.05181	.01055
09	.80911	.00291	.96006	.03194
10 *	.88983	.00001	.94064	.03790
11	.99698	.00001	.87173	.01280
12	.92313	.00002	1.05504	.01881
13	.51862	.00038	1.02749	.04592
14	.99136	.02963	.83166	.02680
15	.99214	.00015	.88588	.01929
16	.99896	.00001	.85678	.00592
17	.99457	.00001	.89462	.00916
18	.95266	.00001	.96158	.01268
19	.78711	.00001	.96652	.01865
20	.94502	.00001	.92721	.01744
21	1.00000	-	.90097	-
22 *	.82002	.00001	.94473	.02968
23	.93176	.00001	.94529	.03873
24	.99977	.00485	1.09645	.00074
25	.99053	.00001	.93123	.00898
26	.94737	.00260	.84927	.05417
27 *	.75755	.00001	.92183	.06297
28	.95404	.01162	.88088	.03508
29	.99367	.00001	.92407	.00827
30	1.00000	-	1.07569	-
31	.48930	.06094	.91040	.16481
32 *	.58516	.00004	.93815	.08324

*** Cross-contractor item-industry composite.**

TABLE A8 - REGRESSION SLOPE ANALYSES, AVPR DEFLATORS

Subfile	R^2	Signif	Slope	SEE
01	.96412	.00001	.90319	.02773
02	.99893	.00001	.82931	.00799
03	.89260	.00001	.92783	.03858
04	.98586	.00001	.84658	.02956
05	.93864	.00016	1.06314	.01487
06	.99882	.01092	.85643	.00808
07	.92026	.00031	.96312	.03462
08	.96814	.00803	1.04437	.01008
09	.85872	.00134	.95105	.03284
10 *	.90488	.00001	.93169	.04038
11	.99774	.00001	.86554	.01163
12	.90477	.00004	1.05315	.02044
13	.44905	.00117	1.02292	.04411
14	.99360	.02548	.83235	.02292
15	.99394	.00010	.88797	.01660
16	.99849	.00001	.84785	.00760
17	.98935	.00001	.88685	.01386
18	.94369	.00001	.95299	.01708
19	.87608	.00001	.95371	.01877
20	.93602	.00001	.91458	.02233
21	1.00000	-	.87736	-
22 *	.81687	.00001	.93437	.03581
23	.92491	.00001	.94537	.04072
24	.99977	.00485	1.09645	.00074
25	.99390	.00001	.90839	.00970
26	.95613	.00198	.83470	.05444
27 *	.84450	.00001	.90427	.05905
28	.95595	.01114	.87556	.03595
29	.99186	.00001	.90159	.01231
30	1.00000	-	1.05884	-
31	.56865	.04164	.89606	.16427
32 *	.71596	.00001	.92240	.07877

* Cross-contractor item-industry composite.

TABLE A9 - REGRESSION SLOPE ANALYSES, NO DEFLATORS

Subfile	R^2	Signif	Slope	SEE
01	.97992	.00001	.92716	.01528
02	.99722	.00001	.84894	.01126
03	.81509	.00001	.95015	.03617
04	.98644	.00001	.86987	.02423
05	.96917	.00003	1.12840	.02047
06	.99992	.00285	.88697	.00163
07	.78023	.00419	.97622	.03997
08	.97544	.00618	1.06526	.01284
09	.74165	.00639	.97185	.02718
10 *	.89164	.00001	.95691	.02702
11	.99017	.00001	.88449	.02071
12	.95625	.00001	1.06579	.01658
13	.87237	.00001	1.05789	.03782
14	.98253	.04220	.86466	.03020
15	.97501	.00084	.90885	.02737
16	.98981	.00001	.87289	.01636
17	.96749	.00001	.91448	.01823
18	.87337	.00001	.97836	.01210
19	.00040	.46870	.99952	.02541
20	.83565	.00001	.95963	.01748
21	1.00000	-	.95125	-
22 *	.76173	.00001	.96973	.01916
23	.79444	.00001	.96020	.05255
24	.99977	.00485	1.09645	.00074
25	.58859	.02205	.97082	.03190
26	.93037	.00398	.86150	.05736
27 *	.46704	.00125	.94718	.07928
28	.95046	.01254	.88975	.03361
29	.83849	.00189	.96187	.02238
30	1.00000	-	1.09385	-
31	.37821	.09691	.92466	.17261
32 *	.30121	.00611	.95972	.09695

* Cross-contractor item-industry composite.

APPENDIX F

COORDINATE TRANSFORMATION REGRESSION RESULTS

The material presented in this appendix is first cited on page 171.

TABLE A10 - COORDINATE TRANSFORMATION REGRESSION RESULTS

Subfile	C	R^2	SEE	F	ln (B_0)	B_1
01	30	.98614	.01690	2347	11.984	-.16587
	100	.99268	.01228	4475	12.222	-.19568
	300	.98555	.01725	2251	12.667	-.24994
02	1	.99895	.00782	13340	11.833	-.27024
	3	.99917	.00695	16893	11.867	-.27567
	10	.99897	.00777	13526	11.980	-.29313
04	1	.98483	.02894	1363	9.360	-.22975
	3	.98543	.02837	1420	9.396	-.23504
	10	.98537	.02842	1414	9.501	-.25079
06	100	.99988	.00277	8011	9.370	-.24242
	300	1.00000	.00045	299819	9.496	-.25583
	1000	.99939	.00611	1647	9.926	-.30110
09	100000	.86806	.02557	32.9	423.44	-35.995
	300000	.86820	.02556	32.9	1369.00	-107.84
10	3000	.99024	.01170	1724	17.202	-1.0196
	10000	.99092	.01129	1854	37.043	-3.0410
	30000	.99069	.01143	1808	99.767	-8.8015
16	1	.99889	.00643	17045	11.456	-.23647
	3	.99912	.00572	21536	11.485	-.24099
	10	.99896	.00621	18256	11.580	-.25549
18	30	.97420	.01092	1171	11.603	-.07600
	100	.98293	.00888	1785	11.714	-.08987
	300	.97842	.00999	1406	11.922	-.11520
19	100000	.77895	.02336	56.4	234.19	-19.517
	300000	.77906	.02335	56.4	745.67	-58.373
20	3000	.98724	.00971	1238	14.594	-.61890
	10000	.98958	.00877	1520	25.189	-1.6898
	30000	.98922	.00893	1468	58.389	-4.7306
22	100000	.97198	.01336	624	149.31	-12.134
	300000	.97228	.01329	631	465.04	-36.112
24	10000	.99986	.00057	7063	-75.683	9.0338
	30000	.99986	.00057	7093	-269.08	26.831
	100000	.99985	.00059	6768	-1018.5	89.122

TABLE A10 - cont.

Subfile	C	R^2	SEE	F	ln (B_0)	B_1
25	10	.99507	.00746	1009	8.671	-.12210
	30	.99579	.00689	1183	8.720	-.12899
	100	.99574	.00693	1169	8.885	-.15163
27	30	.81113	.05902	64.4	8.754	-.13858
	100	.81939	.05771	68.1	8.907	-.15868
	300	.81400	.05857	65.6	9.269	-.20458
29	30	.99074	.01137	535	8.953	-.14012
	100	.99232	.01035	646	9.127	-.16392
	300	.99062	.01144	528	9.595	-.22573
32	10	.65507	.08014	34.2	8.705	-.10526
	30	.65625	.08000	34.4	8.740	-.10974
	100	.65298	.08038	33.9	8.843	-.12275

Regression results for "Best-Fit" curves of form

$$\ln Y_A = \ln B_0 + B_1 \ln (X_1 + C)$$

Subfiles not listed were best described by traditional model (i.e., C = 0 in above equation)

APPENDIX G

RESULTS OF PRODUCTION PARAMETER REGRESSIONS

The material presented in this appendix is first cited on page 173.

TABLE A11 - RESULTS OF PRODUCTION PARAMETER REGRESSIONS

Subfile	Variables	R^2	Adj R^2	SEE	B Values	B Signif
01	X1	.98651	.98606	.00790	B1 = -.20159	.000
	X1+X5	.98946	.98873	.00710	B1 = -.19814 B5 = -.00761	.000 .008
	X1+X5+X3	.99060	.98960	.00682	B1 = -.20299 B5 = -.01012 B3 = -.00352	.000 .002 .075
02	X1	.99963	.99960	.00137	B1 = -.26260	.000
	X1+X3	.99970	.99965	.00129	B1 = -.26380 B3 = -.00108	.000 .154
	X1+X3+X2	.99975	.99967	.00124	B1 = -.26352 B3 = -.00137 B2 = +.00055	.000 .086 .219
03	X1	.94811	.94612	.01280	B1 = -.18203	.000
	X1+X5	.95160	.94773	.01260	B1 = -.18362 B5 = +.00588	.000 .191
	X1+X5+X3+X6	.95932	.95225	.01204	B1 = -.17457 B5 = +.00942 B3 = +.00911 B6 = -.00687	.000 .056 .054 .083

TABLE A11 - cont.

Subfile	Variables	R^2	Adj R^2	SEE	B Values	B Signif
04	X1	.98437	.98362	.02938	B1 = -.22692	.000
	X1+X4	.98770	.98647	.02671	B1 = -.22302	.000
					B4 = -.02666	.031
	X1+X4+X3	.98862	.98683	.02635	B1 = -.22438	.000
					B4 = -.02536	.038
					B3 = +.00812	.229
05 *	X1	.92950	.91540	.01387	B1 = +.07649	.000
	X1+X5	.96486	.94729	.01095	B1 = +.08400	.001
					B5 = -.02654	.115
	X1+X5+X4	.98039	.96079	.00944	B1 = +.08076	.002
					B5 = -.02575	.110
					B4 = +.00594	.221
	X1+X5+X4+X6	.99336	.98008	.00673	B1 = +.08159	.004
					B5 = -.03851	.066
					B4 = +.00677	.135
					B6 = +.01084	.187
	X1+X5+X4+X6+X2	.99873	.99237	.00417	B1 = +.08457	.027
					B5 = -.05649	.121
					B4 = +.00646	.166
					B6 = +.01390	.166
					B2 = -.01270	.288

TABLE A11 - cont.

Subfile	Variables	R^2	Adj R^2	SEE	B Values	B Signif
06 **	X1	.99974	.99947	.00403	B1 = -.23561	.010
11	X1	.99680	.99661	.01324	B1 = -.19900	.000
	X1+X5	.99723	.99688	.01269	B1 = -.19408	.000
					B5 = +.01538	.133
	X1+X5+X4+X6+X3	.99814	.99743	.01153	B1 = -.19097	.000
					B5 = +.02571	.021
					B4 = -.00131	.780
					B6 = -.01834	.040
					B3 = +.01616	.048
	X1+X5+X4+X6+X3+X2	.99831	.99747	.01143	B1 = -.19324	.000
					B5 = +.02302	.040
					B4 = -.00245	.609
					B6 = -.01394	.144
					B3 = +.02028	.030
					B2 = -.00564	.291
12 *	X1	.77289	.74045	.02943	B1 = +.06438	.002
	X1+X4+X3+X2	.93053	.86106	.02153	B1 = +.09770	.003
					B4 = -.03414	.059
					B3 = -.04378	.058
					B2 = +.01933	.076

TABLE All - cont.

Subfile	Variables	R^2	Adj R^2	SEE	B Values	B Signif
13 *	X1	.28944	.24503	.04343	B1 = +.02276	.021
	X1+X4	.39967	.31962	.04123	B1 = +.01741 B4 = -.02779	.074 .118
	X1+X4+X6	.44584	.32709	.04100	B1 = +.02691 B4 = -.02428 B6 = -.01665	.051 .174 .298
	X1+X4+X6+X2	.53505	.39199	.03898	B1 = +.03416 B4 = -.02983 B6 = -.04327 B2 = +.02071	.019 .094 .075 .138
	X1+X4+X6+X2+X5	.63056	.47662	.03616	B1 = +.03781 B4 = -.04487 B6 = -.06606 B2 = +.04179 B5 = +.05441	.009 .025 .019 .031 .104
14 **	X1	.99206	.98411	.02654	B1 = -.27479	.057
15	X1	.99309	.99078	.01871	B1 = -.18089	.000
	X1+X3	.99836	.99673	.01115	B1 = -.21442 B3 = +.06825	.004 .126
16	X1	.99837	.99827	.00242	B1 = -.23262	.000
	X1+X4	.99862	.99843	.00231	B1 = -.23506 B4 = +.00104	.000 .123

TABLE A11 - cont.

Subfile	Variables	R^2	Adj R^2	SEE	B Values	B Signif
17	X1	.98261	.98197	.00838	B1 = -.19098	.000
	X1+X3	.98599	.98492	.00767	B1 = -.19917 B3 = -.00552	.000 .019
	X1+X3+X5	.98817	.98675	.00719	B1 = -.19877 B3 = -.00782 B5 = -.00518	.000 .003 .042
18	X1	.93043	.92794	.00822	B1 = -.09187	.000
	X1+X4	.93995	.93550	.00778	B1 = -.08960 B4 = -.01317	.000 .048
	X1+X4+X6	.94380	.93732	.00766	B1 = -.09692 B4 = -.01033 B6 = -.00298	.000 .131 .193

* Learning slope greater than 100%.

** Limited Data - No Improvement Possible.

NOTE: Intermediate steps, involving entry of variables which did not improve Adjusted R^2 or SEE values, are omitted from this summary.

APPENDIX H

LOG-LINEARITY INVESTIGATIONS

The material presented in this appendix is first cited on page 179.

TABLE A12 - ADJACENT SLOPE SUMMARY

Subfile	Mean	Std Dev	Max	Min
01	.85801	.03910	.93526	.79549
02	.84360	.05080	1.01783	.79003
03	.93754	.12315	1.36317	.79760
04	.87936	.13388	1.19504	.68896
05	1.04756	.05385	1.14395	1.00803
06	.84821	.00583	.85233	.84408
07	.96910	.06564	1.06133	.88004
08	1.14562	.17612	1.34833	1.03012
09	.88336	.10350	.98537	.78341
10 *	.90848	.08644	1.11735	.81197
11	.88603	.07550	.99153	.75715
12	.95357	.09749	1.07074	.83948
13	1.00878	.11164	1.31479	.88977
14	.82371	.03483	.84833	.79908
15	.90254	.03050	.93037	.87046
16	.88842	.08664	1.08399	.76728
17	.86690	.04195	.93232	.77650
18	.91017	.07272	1.02904	.74227
19	.91510	.09643	1.09958	.79975
20	.88145	.05891	1.00000	.80672
21	.89820	-	.89820	.89820
22 *	.88797	.06511	1.00979	.80584
23	.97871	.07729	1.12294	.86648
24	1.05197	.06421	1.09737	1.00657
25	.92038	.03602	.96263	.85810
26	1.16807	.56136	2.00000	.80798
27 *	1.01244	.28341	2.00000	.78408
28	.91074	.07445	.99027	.84271
29	.95074	.11183	1.16858	.84347
30	1.08221	-	1.08221	1.08221
31	1.34170	.60515	2.00000	.81100
32 *	1.06719	.31091	1.95534	.77746
MEANS**	.95542	.11495	1.12584	.84582

* Cross-contractor item-industry composite.

** Excluding composite subfiles 10, 22, 27, and 32.

NOTE: Adjacent slope values greater than 2 arbitrarily set equal to 2.

TABLE A13 - LOG-LINEARITY COMPARISONS:

COEFFICIENT OF DETERMINATION

Subfile	Overall	First	Middle	Last
		Segment		
01	.97015	.98809	-	.99557
03	.90703	.98954	.92639	.98207
04	.98437	.99464	-	.99723
09	.77212	.97447	-	.99980
10 *	.85672	.76824	-	.99414
12	.77289	.91173	-	.99999
13	.28944	.85149	.79061	.96187
18	.95632	.99944	.98907	.92739
19	.73094	.68698	.97485	.00268
20	.90180	1.00000	-	.96867
22 *	.77800	.97309	-	.96689
23	.93582	.95545	.99699	.90470
27 *	.80129	.93107	.77942	.65760
31	.53458	.98303	-	.70482
32 *	.65373	.96045	.78527	.74902

* Cross-contractor item-industry composite.

TABLE A14 - LOG-LINEARITY COMPARISONS:

STANDARD ERROR OF ESTIMATE

Subfile	Overall	First	Middle	Last
		Segment		
01	.02479	.01894	-	.00213
03	.03475	.03401	.00729	.00720
04	.02938	.01793	-	.00389
09	.03361	.00495	-	.00090
10 *	.04482	.01002	-	.00679
12	.02943	.00477	-	.00003
13	.04343	.01712	.03587	.00576
18	.01421	.00233	.00408	.00449
19	.02577	.03983	.00528	.00186
20	.02694	.00000	-	.01217
22 *	.03760	.00160	-	.01127
23	.03790	.04062	.00167	.00269
27 *	.06054	.03588	.01391	.00474
31	.16050	.05385	-	.08746
32 *	.08029	.03752	.03486	.00358

* Cross-contractor item-industry composite.

TABLE A15 - LOG-LINEARITY COMPARISONS:

SIGNIFICANCE

Subfile	Overall	First	Middle	Last
		Segment		
01	.000	.000	-	.000
03	.000	.065	.175	.000
04	.000	.000	-	.000
09	.005	.013	-	.000
10 *	.000	.010	-	.000
12	.001	.003	-	.001
13	.011	.252	.018	.000
18	.000	.015	.000	.000
19	.000	.171	.000	.922
20	.000	.000	-	.000
22 *	.000	.014	-	.000
23	.000	.000	.002	.000
27 *	.000	.000	.047	.050
31	.049	.083	-	.160
32 *	.000	.000	.019	.012

* Cross-contractor item-industry composite.

TABLE A16 - LOG-LINEARITY COMPARISONS:
EXPERIENCE SLOPE

Subfile	Segment			
	Overall	First	Middle	Last
01	.90473	.91492	-	.83437
03	.92951	.90209	1.02459	.86831
04	.85446	.86339	-	.74414
09	.96238	.98102	-	.79342
10 *	.93963	.98378	-	.86762
12	1.04564	.94834	-	1.04574
13	1.01590	.97754	1.11125	.95130
18	.95525	.96971	.94197	.86311
19	.96047	.96903	.84901	.99880
20	.91821	1.00000	-	.88279
22 *	.93877	1.00823	-	.88179
23	.94469	.93540	1.05828	.94015
27 *	.91494	.85555	1.08933	.95396
31	.90476	.83550	-	1.37339
32 *	.93123	.84033	1.27138	.93391

* Cross-contractor item-industry composite.

APPENDIX I

FUTURE PRICE PREDICTIONS

The material presented in this appendix is first cited on page 191.

TABLE A17 - FIRST-BUY PREDICTIONS

Subfile	Actual ($)	Predictions* Relative to Actual ($)/(%) A	B	C	D
01	40,582.82	1,520.00 3.745	642.40 1.583	200.57 .494	207.34 .511
02	23,300.73	20.28 .087	64.77 .278	-	-
03	738.96	10.36 1.402	-6.18 -.836	-6.89 -.932	-6.28 -.850
04	2,283.38	98.34 4.307	102.50 4.489	5.53 .242	13.24 .580
10	6,250.21	425.62 6.810	-	64.41 1.031	-
11	14,572.93	5.92 .041	.02 .000	-	-
13	10,419.08	448.44 4.304	750.73 7.205	35.74 .343	35.74 .343
16	20,054.20	-49.71 -.248	-77.04 -.384	-	-
17	19,985.77	494.31 2.473	364.18 1.822	-	-
18	57,939.81	1,589.85 2.744	1,113.58 1.922	561.83 .970	479.45 .827
20	11,312.63	413.50 3.655	-	175.17 1.548	-
22	11,466.35	572.15 4.990	-	180.71 1.576	-

* A: Overall Regression, Traditional Model

B: Overall Regression, Production Parameter Model

C: Last Log-Linear Segment Regression, Traditional Model

D: Last Log-Linear Segment Regression, Production Parameter Model

TABLE A18 - SECOND-BUY PREDICTIONS

Subfile	Actual ($)	Predictions* Relative to Actual ($)/(%) A	B	C	D
01	40,532.52	1,529.06 3.772	471.42 1.163	179.96 .444	186.90 .461
02	23,245.57	31.87 .137	182.07 .783	-	-
03	740.00	9.08 1.227	-2.10 -.284	-8.40 -1.135	-7.32 -.989
04	2,232.51	121.59 5.446	121.57 5.445	5.44 .244	-15.87 -.711
10	6,023.30	553.57 9.190	-	55.35 .919	-
11	14,571.24	-19.41 -.133	-70.40 -.483	-	-
13	10,327.34	557.24 5.396	463.71 4.490	91.07 .882	91.07 .882
16	20,074.91	-90.29 -.450	-114.01 -.568	-	-
17	19,847.51	558.50 2.814	453.89 2.287	-	-
18	57,623.74	1,857.12 3.223	1,114.20 1.934	751.08 1.303	401.19 .696
20	11,235.64	440.77 3.923	-	179.31 1.596	-
22	11,393.01	612.89 5.380	-	188.43 1.654	-

* A: Overall Regression, Traditional Model

B: Overall Regression, Production Parameter Model

C: Last Log-Linear Segment Regression, Traditional Model

D: Last Log-Linear Segment Regression, Production Parameter Model

TABLE A19 - THIRD-BUY PREDICTIONS

Subfile	Actual ($)	Predictions* Relative to Actual ($)/(%) A	B	C	D
01	40,433.75	1,578.65 3.904	449.27 1.111	193.74 .479	138.79 .343
02	23,249.76	-15.34 -.066	28.59 .123	-	-
03	741.39	7.27 .981	-7.65 -1.032	-10.60 -1.430	-9.26 -1.249
04	2,234.89	108.84 4.870	102.53 4.588	-15.96 -.714	-37.89 -1.695
10	6,036.30	533.64 8.841	-	26.04 .431	-
11	14,569.05	-52.79 -.362	-212.82 -1.461	-	-
13	10,291.36	600.16 5.832	737.23 7.164	112.28 1.091	112.28 1.091
16	20,089.15	-143.96 -.717	-153.57 -.764	-	-
17	19,807.84	566.80 2.861	408.39 2.062	-	-
18	57,570.76	1,898.22 3.297	1,437.70 2.497	773.72 1.344	696.21 1.209
20	10,989.14	578.40 5.263	-	266.81 2.428	-
22	11,161.11	772.72 6.923	-	276.01 2.473	-

* A: Overall Regression, Traditional Model

B: Overall Regression, Production Parameter Model

C: Last Log-Linear Segment Regression, Traditional Model

D: Last Log-Linear Segment Regression, Production Parameter Model

VITA

William Fitch Cheney, IV was born January 5, 19[illegible], and was raised in Storrs, Connecticut. In June of 19[illegible] he graduated from the University of Connecticut, receiving a Bachelor of Science degree in Electrical Engineering and his commission in the U.S. Air Force. His first two active duty assignments as a Communications and Electronics Officer (in Michigan and Thailand) were followed by two assignments as a Development Engineering Officer (in New York and Florida).

In December of 19[illegible] he graduated from the Air Force Institute of Technology, receiving a Master of Science degree in Systems Management. Two more engineering management assignments followed, as a Program Manager at Wright-Patterson Air Force Base, Ohio, and at the Pentagon. In August of 1977 he graduated from Purdue University, receiving the degree of Doctor of Philosophy for his work in the field of Strategic Management. While at Purdue, he was elected to Beta Gamma Sigma.

VITA

Lt. Col. Cheney is currently assigned to the Aeronautical Systems Division, Wright-Patterson Air Force Base, Ohio, as Chief of the Program Division of the Precision Location and Strike Systems Program Office. He resides with his wife Jerry-Ann and six children at 1538 Tabora Trail, Xenia, Ohio 45385.

VITA

William Fitch Cheney, IV was born [redacted] and was raised in [redacted]. [redacted] June of 1959 he graduated from the University of Connecticut, receiving a Bachelor of Science degree in Electrical Engineering and his commission in the U.S. Air Force. His first two active duty assignments as a Communications and Electronics Officer (in Michigan and Vietnam) were followed by two assignments as a Development Engineering Officer (in New York and Florida). PII Redacted

In December of 1967 he graduated from the Air Force Institute of Technology, receiving a Master of Science degree in Systems Management. Two more engineering management assignments followed, as a Program Manager at Wright-Patterson Air Force Base, Ohio, and at the Pentagon. In August of 1977 he graduated from Purdue University, receiving the degree of Doctor of Philosophy for his work in the field of Strategic Management. While at Purdue, he was elected to membership in Beta Gamma Sigma.

Lt. Col. Cheney is currently assigned to the Aeronautical Systems Division, Wright-Patterson Air Force Base, Ohio, as Chief of the Projects Division of the Precision Location and Strike Systems Program Office. He resides with his wife [redacted] and six children at [redacted]

PII Redacted